THE EFFECTIVENESS OF THE VOLUNTARY 33/50 PROGRAM IN INDUCING ADOPTION OF POLLUTION PREVENTION TECHNIQUES AND TOXIC RELEASE REDUCTION

BY

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DISSERTATION

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Abstract

This dissertation consists of three essays that empirically investigate the role of regulatory pressures, voluntary 33/50 program and information spillover on firms' environmental performance. First, we examine the extent to which participating in the 33/50 program led to a reduction in 33/50 releases. Second, we examine the extent to which program participation motivated the adoption of Pollution Prevention (P2) technology, and whether learning from peers increased the adoption of P2 technology by a facility after controlling for the effects of program participation and regulatory pressures. Last, we examine the extent to which program participation caused an increase in recycling and whether the adoption of P2 technology was inversely related to changes in recycling and releases of 33/50 chemicals. To answer these questions, we use facility-level information on program participation, toxic emissions and P2 adoption for more than 7000 facilities that were eligible for the program over the period of 1988-1995. We find that program participants had 14.8% to 23.7% higher rate of reduction in 33/50 releases than non-participants, after controlling for industry effects, time trend and other regulatory pressures. We also find that program participants on average adopted 1-1.2 more P2 technologies than non-participants for 33/50 chemicals, but did not significantly increase the number of P2 technologies adopted for other TRI chemicals. Additionally, the adoption of P2 was positively affected by information spillovers from other facilities in the same industry. Although program participants adopted more P2 technologies for 33/50 chemicals, the effects of P2 on recycling and releases of 33/50 chemicals were not statistically significant.

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Chapter 1 Introduction

Pollution control in the U.S. has been achieved mainly through a command and control regulatory system. Difficulties in developing regulations to control numerous pollutants emitted by firms have led to an interest in using more cost effective incentive-based policy instruments to promote green stewardship among firms. One of these instruments is information disclosure through the Toxics Release Inventory (TRI). TRI was established in 1986, under the provisions of the Emergency Planning and Community Right-to-Know Act (EPCRA), to provide publicly available information on toxic chemicals. "Manufacturing facilities included in SIC codes 20 through 39 are required to submit an annual toxic chemical release report that includes locations and quantities of chemicals stored on-site, transferred to various facilities and released to environmental media under the following conditions: if they have 10 or more full-time employees and if they manufacture, process, or use specified chemicals in amounts greater than threshold quantities"[1] (U.S. Environmental Protection Agency, 2004). The US EPA compiles these reports and makes them publicly available. The current TRI database contains chemical, media, and location-specific information for 666 toxic chemicals across seven industry sectors[2], and has been widely used by economic analysts as one indicator of a firm's environmental performance (Banzhaf and Walsh, 2008; Hamilton, 1998; Khanna, 2001). Existing studies show that the public information disclosure of TRI has increased the visibility of polluters, and thus created incentives for firms to undertake voluntary efforts to reduce pollution in order to appeal to green consumers and shareholders and to avoid regulatory scrutiny (Arora and Cason, 1996;

[1] Process more than 25,000 pounds in aggregate and use more than 10,000 pounds of any TRI chemicals.
[2] http://www.epa.gov/TRI/trichemicals/index.htm; facilities from four more industry sectors were added in 1998.

Arora and Gangopadhyay, 1995; Khanna, 2001; Konar and Cohen, 2001; Sam, 2009; Sam et al., 2009).

In addition to EPCRA, the US Congress passed the National Pollution Prevention Act (PPA) of 1990. It recognizes the limitations of the existing environmental regulatory framework that emphasizes media-specific end-of-pipe pollution control and seeks to promote a more holistic approach to controlling pollution through Pollution Prevention (P2). The PPA also declares the preferred approach in the pollution control hierarchy to be P2. Specifically, it states that "pollution should be prevented or reduced at the source whenever feasible, pollution that cannot be prevented should be recycled in an environmentally safe manner whenever feasible, pollution that cannot be prevented or recycled should be treated in an environmentally safe manner, and disposal or other release into the environment should only be employed as the last resort and should be conducted in an environmentally safe manner"(U.S. Environmental Protection Agency, 1990). Though P2 has received greater policy emphasis, the adoption of P2 technology remains voluntary. To measure the progress in reducing wastes through P2, the PPA has required additional reporting of waste management and source reduction activities at a chemical and facility- specific level in the TRI. Following the passage of the PPA, the EPA also established a P2 information clearinghouse to facilitate the exchange of information.

Another mechanism to encourage the P2 ethic and accomplish pollution reduction is through public voluntary environmental programs. The 33/50 program was the first public voluntary program introduced by the EPA. It targeted at 17 toxic chemicals listed in the TRI that were widely used by US manufactures. The 33/50 refers to the goal of the program that was to reduce the national aggregate releases of the 17 chemicals by 33% by 1992 and by 50% by 1995. The program provided public recognition on participants' voluntary efforts to reduce those

otherwise unregulated pollutants. It not only gave flexibility to the participants on the methods and extent of reduction achieved, it also sought to instill a P2 ethic among firms by encouraging them to modify their production process, substitute input chemicals, and adopt practices to reduce their emissions through source reduction (Khanna, 2006).

Existing studies have focused on the 33/50 program because it is the first public voluntary program and its outcome is measurable through the TRI. Most research agrees that the 33/50 program provided incentives to firms to undertake pollution control efforts, in order to signal good faith to the regulators, to appeal to green consumers, and to avoid boycotts (Arora and Cason, 1996; Gamper-Rabindran, 2006; Innes and Sam, 2008; Khanna and Damon, 1999; Sam, et al., 2009; Videras and Alberini, 2000; Vidovic and Khanna, 2007). However, empirical evidence on the effectiveness of the 33/50 program in reducing toxic releases has been mixed (Khanna and Brouhle, 2009). The mixed evidence on the effectiveness of the 33/50 program has led to the arguments against voluntary programs in general. The key arguments are that programs participants took credit for what they would have done anyway in the absence of the programs. In other words, voluntary programs have not caused changes in firms' environmental behaviors.

Some scholars have recently proposed that eliminating voluntary programs from the policy options may be premature. It could be the case that the best environmental practices had been disseminated from participants to non-participants, which made comparing the pollution reduction between program participants and non-participants difficult (Lyon and Maxwell, 2007). They suggest that policy makers may design voluntary programs to enhance such potential dissemination of pollution prevention technology in the future.

While the 33/50 program is the most studied voluntary program, this dissertation improves the understanding of the role of voluntary programs in reducing pollution and

promoting the adoption of environmental technology in the following ways. First, existing studies have used data aggregated at the firm level or assumed that all facilities were program participants if their parent companies participated in the program. However, only 20% of the facilities belonging to participating firms actually participated in the program, indicating great heterogeneity among facilities within the same parent company. In this dissertation, we relax this assumption made by the previous studies and re-evaluate the effectiveness of the 33/50 program using facility-level information on program participation and toxic emissions. We show that using the assumption made by previous studies leads to attenuated estimates of program impacts. Thus, we contribute to the research by showing the importance of conducting the analysis at a highly disaggregated level.

Second, the 33/50 program was established to promote the P2 ethic among firms, but none of the existing studies have examined the extent to which participating in the 33/50 program had induced the adoption of P2 technology and whether program participants motivated their neighboring facilities to adopt P2 technology. Furthermore, unlike end-of-pipe technologies that are more likely to be available off the shelf, P2 includes modification of production processes and substitution of toxic with non-toxic or less toxic materials. These activities are more likely to be operation and facility-specific. These operational challenges could increase the search and information costs thus discourage the adoption of P2 technology. However, other facilities' experience on the adoption of P2 technology could reduce the informational costs, thus promote the adoption of P2 through information spillovers. This is the first study to investigate the role of information spillovers in motivating the adoption of P2. We contribute to the literature by examining the extent to which the adoption of P2 technology was motivated by prior P2

experience of peer facilities and examine whether higher levels of program participation by neighboring facilities motivated P2 adoption.

Third, while the existing studies on the 33/50 program have focused on the incentives for participation and the effectiveness of the program, few have examined the mechanisms through which the reduction of 33/50 emissions was achieved. Program participants might have used P2 to reduce emissions at source or used other abatement methods that could result in an increase in recycling. Though the use of the recycling method is preferable to direct on-site releases of toxic chemicals, it is lower in the pollution control hierarchy than P2. An increase in recycling could indicate that program participants did not undertake fundamental changes in their environmental management practices, but simply shifted the pollutants from direct release to recycling facilities despite the emphasis of the 33/50 program on P2. This dissertation fills the gap in the literature gap by examining the mechanisms by which firms reduced their 33/50 releases; whether by recycling or prevention at source.

The rest of the dissertation is organized as follows: Chapter 2 evaluates the effectiveness of the 33/50 program in reducing toxic releases of the 33/50 chemicals. Chapter 3 examines the extent to which the adoption of P2 technology was motivated by the 33/50 program and whether prior P2 experience of peers increased the adoption of P2 technology. Chapter 4 examines the extent to which program participation led to changes in recycling and whether P2 adoption led to reduction in releases and increase in recycling of 33/50 chemicals. Chapter 5 summarizes findings and provides policy implications.

Chapter 2 Re-assessment of the Impact of EPA's Voluntary 33/50 Program on Toxic Releases

2.1 Introduction

Pollution control in the U.S. has typically relied on command-and-control environmental regulations that are costly to enact, monitor and enforce. Since the 1990s there has been greater emphasis on voluntary programs to reduce releases of unregulated pollutants, such as toxic releases in an effort to find less adversarial and more cost-effective approaches to reduce toxic pollution that can be implemented without legislative delays. This followed the passage of the Emergency Planning and Community Right to Know Act of 1986, which required manufacturing facilities to report their annual on-site releases and off-site transfers of specified toxic chemicals to the Toxics Release Inventory (TRI). Though firms are not penalized for reporting large TRI emissions, the public disclosure of TRI has raised awareness among regulators and the public about the magnitude of the toxic pollution problem and imposed reputational costs on firms listed as large toxic polluters (Hamilton, 1998).

The 33/50 program was the first voluntary program established by the U.S. EPA. It was established in 1991 with the goal of reducing the aggregate releases of 17 toxic chemicals[3] by 33% by 1992 and by 50% by 1995, relative to the level in 1988. Firms had flexibility in the extent of reduction they achieved and in the methods they chose to reduce their releases. Observed data suggest that the program was successful in attracting participation from 1294 companies, which is 13% of all eligible firms. Those participating companies generated more

3 The 17chemicals are: 1,1,1-trichloroethane, benzene, cadmium & cadmium compounds, carbon tetrachloride, chloroform, chromium and chromium compounds, cyanide compounds, dichloromethane, lead and lead compounds, mercury and mercury compounds, methyl ethyl ketone, methyl isobutyl ketone, nickel and nickel compounds, tetrachloroethylene, toluene, trichloroethylene, and xylenes. 1,1,1-trichloroethane and carbon tetrachloride are classified as ozone depleting substances (U.S. Environmental Protection Agency, 1997).

than 60% of releases of 33/50 chemicals (hereafter referred to as 33/50 releases) in the U.S. in 1988. The EPA reported that the aggregate releases of 33/50 chemicals declined by 55% by 1995 relative to 1988 with 72% of this reduction occurring after 1991, suggesting that the program exceeded its goals (U.S. Environmental Protection Agency, 1997).

The extent to which this reduction is attributed to program participation can, however, be questioned for several reasons. First, two of the 17 chemicals were considered ozone depleting (OD) chemicals and were going to be phased out by 1996 under the Montreal Protocol. The anticipated regulation could have created incentives for some firms to achieve early reductions even in the absence of the 33/50 program. Second, by using 1988 as the baseline for measuring emissions reductions, the program created incentives for firms that had already achieved reductions prior to the 33/50 program to participate and obtain credit for those reductions. These firms may have initiated actions to reduce releases prior to participation following negative publicity accompanying the public disclosure of TRI data that was independent of their program participation decision.

Several studies have examined the effectiveness of the 33/50 program in reducing 33/50 releases but yielded mixed results (discussed in the next section). The purpose of this paper is to re-assess the impact of the 33/50 program on 33/50 releases using data on program participation at the facility level for all eligible facilities for the 1988-1995 period. We use a panel data Generalized Method of Moments (GMM) framework to incorporate the facility-specific unobserved effects, potentially endogenous program participation decision and the dynamics of pollution generation. In undertaking this analysis we control for any time trend in emissions and for the synergistic effects of other regulations. We examine the effects of the program on all 33/50 chemicals and separately for the OD and non-OD chemicals. We also consider its impact

on the toxicity weighted releases of 33/50 chemicals.

In addition to using the GMM framework, this study differs from existing studies in several ways. First, we examine the impact of the 33/50 program using data on participation at the facility level. This is in contrast to other studies that were conducted at firm level and/or assume that all facilities belonging to a participating parent company participated in the program. The EPA considered a parent company as a program participant, as long as it had at least one facility participating in the program. Our information on facility level participation reveals that only 23% of the facilities belonging to 33/50 companies actually participated in the program. We find that 553 out of the 1203 participating firms had multiple plants. These multi-plant firms had 25 facilities on average; of these only 3 facilities participated in the program, on average. Only 30 out of the 553 multi-plant firms had all their facilities participated in the program. As discussed below, we find that only 1,335 facilities out of the 5,595 facilities that belong to the 33/50 parent companies actually participated in the 33/50 program (hereafter 33/50 facilities). Earlier papers have thus overestimated the number of facility participants by more than four-fold. Second, our data include a much larger sample of eligible facilities compared to previous studies that have focused on S&P 500 firms or on certain industries. Third, we examine if the program's impact on the two OD chemicals differed from that for the non OD chemicals.

2.2 Related Literature

Several papers have sought to explain the incentives for participation in voluntary programs and their effectiveness in improving environmental performance (see reviews in (Khanna and Brouhle, 2009) and (Alberini and Segerson, 2002; Khanna, 2001)). These studies show that regulatory pressures, due to current and anticipated regulations, as well as the threat of environmental liabilities motivated firms to participate in the 33/50 program (Arora and Cason,

1995; Gamper-Rabindran, 2006; Innes and Sam, 2008; Khanna and Damon, 1999; Sam, et al., 2009)). Pressure from the firm's stakeholders, such as consumers, communities and environmental interest groups, also created incentives for participation in the 33/50 program to improve the environmental reputation of the firm (Arora and Cason, 1996; Gamper-Rabindran, 2006; Innes and Sam, 2008; Khanna and Damon, 1999; Sam, et al., 2009; Videras and Alberini, 2000; Vidovic and Khanna, 2007). Studies also show that firms that were included in the first group invited by the EPA to participate in the 33/50 program (because they were among the largest emitters of 33/50 chemicals) were more likely to participate in the program (Arora and Cason, 1996; Gamper-Rabindran, 2006; Innes and Sam, 2008; Khanna and Damon, 1999; Sam, et al., 2009). Evidence of free-rider behavior by firms that had achieved reduction in releases prior to the start of the 33/50 program in 1991 is mixed. Vidovic and Khanna (2007) find that firms that had achieved a larger absolute reduction in their 33/50 releases during 1988-1990 were more likely to participate in the program. Gamper-Rabindran (2006) finds this to be the case only in some sectors. Innes and Sam (2008), Sam et al. (2009), Khanna and Damon (1999) and Arora and Cason (1996) find no evidence of free-rider behavior.

Studies that analyze the effectiveness of the 33/50 program are reviewed in Khanna and Brouhle (2009). Khanna and Damon (1999) study the impact of program participation on the chemical sector and find that the expected reduction of 33/50 releases that can be attributed to program participation is 27.92% relative to the pre-program level over the period of 1991-93. Vidovic and Khanna (2007) examine the effects of the program over the period 1991-95 for a broader set of sectors and argue that participation in the program had no effect if prior reductions in pollution achieved before the start of the program and time and fixed-effects are taken into account. However, Innes and Sam (2008) find that 33/50 participation significantly reduces

33/50 releases as well as toxicity weighted 33/50 releases, even after controlling for time and industry effects, with the statistically significant reduction occurring at the start of the program in 1991-1992. They estimate that the cumulative reduction in 33/50 releases over the period of 1991-1995 due to the program is over 45% of the average emissions of participants in year 1990. More recently, Sam et al. (2009) find that even after controlling for other voluntary activities a firm might undertake, such as adoption of Total Quality Environmental Management, program participation had a statistically significant negative impact on 33/50 releases not only during the program years but also over the 1996-1998 period, after it ended. Gamper-Rabindran (2006) focuses only on the 15 non-ozone depleting chemicals, arguing that the two OD chemicals were due to be phased out anyway under the Montreal Protocol. She conducts industry-specific analysis and finds that the impact of the program on 33/50 releases and health-indexed 33/50 releases from the 15 chemicals varied by industry and media. The program's impact on 33/50 releases ranged between -51% in the fabricated metal sector to +170% in the chemical sector over the period of 1991-1995. Similarly, the program's effects on toxicity weighted releases differ across industries, ranging from -390% in the fabricated metal sector to +110% in the chemical sector. The analysis, however, does not shed light on the reasons for these differing impacts of the program across industries. The broad conclusion from this literature appears to be that, at least in some sectors, the 33/50 program led to reduction in releases.

These studies have examined the impact of participation using firm-level data that considers a firm as a participant if even one facility of that firm participates in the program. Gamper-Rabindran (2006) analyzes the effectiveness of participation at the facility level but assumes that all facilities belonging to a participating parent company (hereafter 33/50

companies) participated in the program [4]. Additionally, these studies have modeled participation decisions using probit models with cross sectional information about participation in the first year of the program,1991/1992 (Gamper-Rabindran, 2006; Innes and Sam, 2008).[5] Similarly, Vidovic and Khanna (2007) assume that all participants joined in 1991. Unlike these studies, Khanna and Damon (1999) estimate a cross sectional probit model but incorporate information on program participation for each year from 1991 to 1993[6]. In this paper, we use firm-specific information on the time of participation to obtain the time of participation for each facility. We, however, assume that the facilities participated at the same time as their parent companies. We then use a pooled probit model with clustering at the facility level to estimate the program participation decision. We also examine if the effect of the program differed over the five years and whether the program continued to have an effect after 1995.

Previous studies on effectiveness of this program have used a two-step procedure to correct for self-selection into the program. Program participation is modeled using a probit model and the fitted probability or inverse mills ratio is included directly in the second step estimation on 33/50 releases (Gamper-Rabindran, 2006; Innes and Sam, 2008; Khanna and Damon, 1999; Vidovic and Khanna, 2007). To obtain consistent parameter estimates for the program outcome regression, the first-step participation model needs to be correctly specified (Angrist, 2001) and the standard errors in the outcome equation need to be corrected using boostrapping procedures (Innes and Sam, 2008; Vidovic and Khanna, 2007). We avoid these

[4] The sample analyzed by Gamper-Rabindran consists of 3261 facilities and is much smaller than that used in this paper which includes 8756 facilities.

[5] Gamper-Rabindran (2006) defines a 0/1 dummy variable (equal to one for a participant and zero otherwise) for year 1991. Innes and Sam (2008) estimate the program participation decision for year 1992. Instead of including the participation variable as 0/1 variable for year 1992 only, they construct four participation variables in the releases model. Each of these is defined as a 0/1 variable for a firm for each of the remaining years of the program (1992-1995), thus they measure the incremental effect of each year's participation on 33/50 releases.

[6] The cross sectional data set is compiled such that firms are eliminated from the subsequent years once they participated in the program.

concerns by using the predicted probability of participation as an instrumental variable in the second-step outcome regression (Wooldridge, 2002).

Furthermore, previous studies have either excluded the releases of the two OD chemicals (Gamper-Rabindran, 2006; Sam, et al., 2009) (implicitly assuming all reduction of OD chemicals were due to the mandatory phase-out), or aggregated all 17 chemicals (assuming the impact of the 33/50 program is the same across the OD and non-OD chemicals). In contrast, we include specifications that consider the two groups of chemicals separately to examine any differential effect of the program across chemicals. In one specification we also compare the effects of mandatory regulations (under the Montreal Protocol) to those of the voluntary 33/50 program on 33/50 releases.

2.3 Empirical Framework

Our empirical analysis is based on the premise that a rational facility chooses its level of pollution generation and whether or not to participate in a voluntary program, such as the 33/50 program, simultaneously. There are several reasons why it could be motivated to participate in the 33/50 program and/or voluntarily reduce its toxic releases. These include a desire to preempt more stringent regulations, to signal good faith effort to regulators and public, and to obtain public recognition for participation and reduce the negative publicity due to disclosure of its toxic releases in the TRI. Therefore, bigger polluters that face greater regulatory pressures and compliance costs are more likely to participate in the program (Innes and Sam, 2008; Khanna and Damon, 1999; Vidovic and Khanna, 2007). Participation, however, does not guarantee that a facility will actually reduce its 33/50 releases, since a participant was neither required to commit to any particular level of reduction nor penalized for not making any reductions. Moreover, some facilities might have begun making changes to their operations even before the program was

initiated to reduce negative publicity. They might have joined the program simply to get credit for reductions they were going to make anyway. Additionally, non-participants may have incentives to reduce releases to avoid future compliance costs. It is also possible that the reduction in 33/50 releases was largely due to the mandatory phase out of the OD chemicals and not the voluntary 33/50 program.

The effect of program participation might differ across chemicals. The aggregated releases of the two OD chemicals were only about 14% of the total 33/50 releases in 1988 (U.S. Environmental Protection Agency, 1997). But releases of the OD chemicals experienced the highest percentage reduction (86%) from 1988 to 1995. During the same period, releases of the non OD chemicals decreased by only 40%. Since facilities knew that the OD chemicals were to be phased out, even non-participants in the program would have incentives to reduce their releases of these chemicals while not having similar incentives to reduce the releases of the non-OD chemicals. Thus, the effect of the program on releases of these two types of chemicals could differ due to differences in other factors motivating facilities to reduce these two types of releases.

The effects of the program might also differ across chemicals with different toxicity. Some of the 33/50 chemicals such as lead, mercury and cadmium have high toxicity and carcinogenicity and have been identified as priority chemicals for reduction by the U.S. EPA. Facilities using highly toxic 33/50 chemicals are more likely to undertake voluntary efforts to reduce emissions of these chemicals to avoid future liabilities and to respond to stronger pressures from environmental groups (Maxwell, et al., 2000) and local communities (Gamper-Rabindran, 2006).

We undertake this analysis by hypothesizing that the *ith* facility's emissions at time *t*, Y_{it},

are determined by a vector of observed exogenous facility-specific variables, X_{it} (such as a facility's production technology, level of output produced, input and output prices), its program participation decision, P_{it}, and unobserved facility-specific fixed effects. Emissions are also affected by managerial, technical and organizational features of a facility's operations which may change slowly over time and are not always observable. Output, managerial characteristics and technology are likely to change slowly and be autoregressive and are unobservable. We proxy their effects by including lagged emissions. For those reasons, we expect to see path-dependence in the 33/50 releases and specify the regression model as follows:

$$\Delta y_{it} = \rho \Delta y_{it-1} + \beta_1 \Delta X_{it} + \theta P_{it} + \beta_2 d_i + \beta_3 \lambda_t + \Delta u_{it} \ , \ \text{t=1991,..., 1995} \qquad [2\text{-}1]$$

where y_{it} is 33/50 releases, $\Delta y_{it} = y_{it} - y_{it-1}$, $\Delta y_{it-1} = y_{it-1} - y_{it-2}$ $\Delta X_{it} = X_{it} - X_{it-1}$, $\Delta u_{it} = u_{it} - u_{it-1}$[7].

The binary participation variable is $P_{is} = 1$ for $t \geq s$ if facility joined the program in year s, and $P_{is} = 0$ otherwise. The variable, λ_t captures the time trend, and d_i represents time-invariant industry dummies and variables that control for location effects. The coefficient θ for program participation can be interpreted as the difference in the rate of release reduction between participants and non-participants when y_{it} is taken in log form.

To correct for the endogeneity of $P_{it,}$, we use a two-step procedure[8]. First, like previous studies we obtain the predicted probability of participation by estimating a discrete choice model of program participation in the first step (as described by equation [2-2]). Second, we use this as an instrument to estimate the impact of participation on change in releases together with earlier

[7] It is possible that the error term still contains individual specific effects since we did not first difference all the explanatory variables.

[8] This two-step procedure ensures that the standard errors obtained in the second step are asymptotically valid, and it is robust to misspecifications of the first step model (Wooldridge, 2002, p. 623).

lags of the dependent variable to control for endogeneity of the lagged dependent variable in equation [2-1].

$$P_{it} = \delta_1 x_{it} + \delta_2 d_i + \delta_3 \lambda_t + \delta_4 z_{it} + \varepsilon_{it} \qquad [2\text{-}2]$$

where $P_{it} = 1$ is observed iff $x_{2it}'\beta + z_{it}'\delta + \varepsilon_{it} > 0$; $P_{it} = 0$ otherwise; t=1991,…,1995. To ensure identification of the parameters in equation [2-1] it is important to have some variables z_{it} that are hypothesized to influence participation but are uncorrelated with the change of releases. In the next section we will describe the choices of these variables in detail.

Since we have a relatively short panel with lagged dependent variable, we could use 2SLS by Anderson and Hsiao (1981) to estimate equation [2-1], where y_{it-2} is used as an instrument, since $E(y_{it-2}\Delta u_{it}) = 0$ and y_{it-2} is correlated with Δy_{it} (Andersen and Hsiao, 1981). Additional instruments are available when the panel has more than 3 period observations, which means $(y_{it-2}, ...y_{i1})$ can be used as instruments in the first-differenced equation for period t. However, 2SLS is not asymptotically efficient, even if the complete set of instruments is used for each equation at each time (Arellano and Bond, 1991). Arellano and Bond recommend using a generalized method of moments (GMM) estimation procedure for equation [2-1] that uses two-year and earlier lags of the dependent variable as GMM instruments for the lagged dependent variable with the following instrument matrix:

$$Z_i = \begin{bmatrix} y_{i1} & 0..... & 0 & 0 \\ 0 & y_{i1} & y_{i2}..... & 0 \\ ..... & ..... & . & . \\ 0 & 0 & 0 & y_{i1.....}y_{i,T-2} \end{bmatrix}$$

, where each row corresponds to the first differenced equation for periods *t=3,4,..T,* for each observation *i.* To reduce small sample bias , we limit the number of GMM instruments to two-year lags of the dependent variable as

suggested by Roodman (Roodman, 2006) and others. The resulting instrument matrix has the following form: $Z_i = \begin{bmatrix} y_{i2} & 0..... & 0 & 0 \\ 0 & y_{i3} & 0..... & 0 \\ . & ..... & . & . \\ 0 & 0 & 0 & y_{i,T-2} \end{bmatrix}$, where each row corresponds to the first differenced equations for period *t=1991 , 1992, 1993..1995*. Thus, 33/50 releases in 1989 serve as an instrument for releases in 1991 and so on. [9] This leads to an instrumental variable matrix consisted of a total of six columns, with five columns of y_{it-2} as instrument for each period of *t =(1991..1995)* ; and one column of predicted probability obtained from estimating equation [2-2]. Since we have two endogenous variables, Δy_{it-1} and P_{it} , the number of over identified conditions(restrictions) is thus 6-2=4.

To avoid concerns that releases during program years could be serially correlated, we also estimate alternative models using pre-program releases (1988 and 1989) as instruments instead of y_{it-2} for releases during the program years. Releases in 1988 and 1989 happened prior to the program's initiation and were uncorrelated with the error terms for the period of 1991 to 1995. This results in 9 over-identified conditions (two columns instruments for each period of *t*, plus one column of predicted probability, and minus two endogenous variables).

We use the Hansen's J statistics to test for orthogonality of the instruments and the Kleibergen-Paap rk statistics to detect weak correlation/identification between the instruments and the endogenous variables. We also test for second-order auto-correlation of the errors in the releases models using tests suggested in (Wooldridge, 2002). Results of these tests are reported and discussed in section 2.7.

[9] Our results remain robust to the number of lags included in this instrumental variable matrix.

2.4 Variable Construction

2.4.1 Dependent Variable

The dependent variable in equation [2-1] is constructed by taking the logarithm of 33/50 releases at the facility level and then taking its first difference. The 33/50 releases include onsite releases to air, water, land, and off-site transfers for treatment and disposal of all 33/50 chemicals emitted by a facility. In other models we evaluate the program's effect on releases of OD chemicals, non-OD chemicals and on toxicity weighted 33/50 releases. All of those variables are also in logarithm and then first differenced. The dependent variable in equation [2-2] takes a value of 1 if a facility participated in the program in a given year and 0 otherwise.

2.4.2. Explanatory Variables

Our key explanatory variables included in both equation [2-1] and [2-2] are proxies for regulatory pressures faced by facilities, industry, time and location effects. Industry-specific effects are controlled by including ten industry dummies, classified by facility's primary 2-digit SIC code. Time effects are controlled by time dummies for 1991-1995. Variables to control for location effects include C*ounty Median Income* of the county in which a TRI facility is located (in logarithm). Since these variables do not vary over time, we include them in levels in each of the two steps of estimation.

As proxies for existing and anticipated costs of compliance with regulations at the facility level, we include the *Number of Inspections* for compliance with air pollution regulations and the *HAP-TRI* ratio, defined as the percentage of releases of hazardous air pollutants (HAP[10]) chemicals in total TRI releases. Facilities that were inspected more frequently previously were more likely to show good-faith efforts to the regulators by participating in the voluntary program

[10] 189 toxic chemicals are identified as Hazard Air Pollutant Chemicals and include the 17 33/50 chemicals.

and reducing releases (as in, Gamper-Rabindran, 2006; Sam, et al., 2009), possibly to reduce the frequency of inspections in the future (as found to be the case by (Innes and Sam, 2008)). HAP chemicals were expected to be regulated from year 2000 onwards with the imposition of Maximum Available Control Technology (MACT) standards. Firms with a higher value of this ratio were likely to face greater costs of compliance in the future and thus have greater incentives to participate in the 33/50 program and reduce releases ahead of time using flexible methods (Gamper-Rabindran, 2006; Khanna and Damon, 1999; Vidovic and Khanna, 2007). Both *HAP-TRI* ratio and *Number of Inspections* vary over time and are lagged by one year and then first-differenced.

We also include proxies for the stringency of the existing regulatory climate of the county. These include the *County Non-attainment Status* for the 1991-1995 period. As per the 1977 Clean Air Act Amendments, every county in the US is designated annually as being in attainment or in non-attainment with national air quality standards for six criteria air pollutants: carbon monoxide, sulfur dioxide, total suspended particulates, ozone, nitrogen oxide and particulate matter. Facilities in counties that are in non-attainment are expected to be subjected to more stringent controls (Greenstone, 2002), with the degree of stringency varying with the severity of pollution (basic, marginal, moderate, serious, two categories of severe and extreme) (Tietenberg, 2006). These facilities may be more likely to undertake voluntary efforts to improve environmental performance. Khanna et al. (2009) find that firms located in non-attainment counties were more likely to voluntarily adopt pollution prevention techniques to reduce toxic releases. We aggregate the total number of pollutants for which the county was in non-attainment status in a given year, then use its first difference as a proxy for local regulatory stringency.

The voting record of Senate and House of Representatives on environmental bills may

reflect the political climate in the state, which may influence the stringency of future state environmental regulations. We include the first difference of the *State LCV Scores of* environmental-friendly bills passed by the state legislature from 1991 to 1995 (League of Conservation Voters, 2007). We also include its squared term to allow for non-linear effects.

2.4.3. Excluded Instruments for Program Participation

To ensure identification of the parameters in equation [2-1], we use as instruments those variables that were correlated with the facility's participation decision but not with its change in releases during the program period. These variables have also been shown by previous studies (as discussed below) to influence firm-level participation and are not likely to be correlated with a facility's releases. These variables are included as explanatory variables in the probit model of participation in equation [2-2] but are excluded from equation [2-1]. These variables include a dummy for whether the facility belonged to a firm in the first invitation group, change in releases of the firm prior to the program (1988 to 1990) and the percentage of a firm's TRI releases emitted by a facility prior to the program (in year 1988 or 1989). We do not include any (program year) emissions variables either at the firm or facility level as instruments since those could be influenced by similar variables as the facility's change in releases. We describe these instruments in greater detail below.

Our first instrument is a dummy variable that takes a value of 1 if a facility belongs to one of the 517 parent companies that were the first to receive an invitation to join the 33/50 program in March 1991. Subsequent invitations to eligible firms were sent out by the EPA in July 1991, July 1992, Jan 1993 and 1994, to encourage participation in the 33/50 program. Of the top "500 firms" in the first invitation group, 64% participated in the program. Earlier studies have found that firms belonging to the *First Invitation Group* were more likely to participate in

the 33/50 program (Arora and Cason, 1996; Gamper-Rabindran, 2006; Khanna and Damon, 1999; Vidovic and Khanna, 2007). We also find that 12.6 % of the facilities belonging to the firms in the first invitation group participated in the 33/50 program[11]. The variable *First Invitation Group* can be considered exogenous to the change in releases at the facility level except through program participation because the formation of invitation group preceded the initiation of the 33/50 program and was based on the ranking of top companies by the 1991 Fortune Magazine (Gamper-Rabindran, 2006; Khanna and Damon, 1999). Moreover, while the first invitation group is defined at the parent company level, the dependent variable Δy_{it} is defined at the facility level. Since parent companies typically have multiple facilities not all of which participated, the change in 33/50 releases at the facility level is not likely to be directly impacted by the invitation to the parent company and it's decision to enroll in the program except through the facility's participation decision.

We include the share of a facility's total TRI releases in the total TRI releases of the parent company prior to program participation as an explanatory variable since that might have influenced the selection of facility for program participation within the firm. We measure this *Share in Total TRI Releases of Parent Company* in 1988 or in 1989 depending on data availability. While a larger share in a parent company's total TRI releases prior to the program is likely to influence participation in the program, it is unlikely to directly influence subsequent reductions by a facility in a sub-set of the TRI releases (33/50 chemicals) unless it is through the facility's participation decision.

[11] One of the studies (Arora and Cason, 1996) only observe the assignment of the first invitation group for participating companies; thus a selection model to predict the likelihood of being in the first invitation group is estimated and the predicted value is used in their program participating model. In contrast, we are able to identify both participants and non-participants in our dataset for all companies that were in the first invitation group, thus we do not need to control for selection in the first invitation group in our study.

In addition, earlier studies at the firm level have hypothesized that a firm is more likely to participate in the 33/50 program if it had achieved greater reduction in 33/50 releases prior to the program (during years 1988 to 1990) (Arora and Cason, 1996; Innes and Sam, 2008; Khanna and Damon, 1999; Vidovic and Khanna, 2007). The empirical finding on the effect of prior reduction in 33/50 releases on program participation is mixed. Arora and Cason (1996), Khanna and Damon (1999), Vidovic and Khanna (2007) found that the prior change in 33/50 releases was not significant in the program participation model[12] while Innes and Sam found that prior reduction in 33/50 releases significantly increased the likelihood of program participation. Unlike, Khanna and Damon (1999) and Innes and Sam (2008), Vidovic and Khanna (2007) include this variable in the second stage outcome equation and find that firms that had undertaken a larger reduction prior to the program also reduced more 33/50 releases during the program; the program's effect is found to be insignificant after including the prior change in 33/50 releases in the second-stage release model.[13] We estimate specifications that include and exclude this variable as an instrument to examine the robustness of our results. We define *Firm Prior Change in Releases* as the change in releases achieved by a firm prior to the program in our program participation model (that is, 33/50 releases in 1990 minus the releases in 1988).

2.5 Data Description

The TRI contains chemical and facility specific information on toxic releases to different environmental media, from which, we calculate the 33/50 releases, the HAP releases and total TRI releases per facility. It also provides information on SIC codes, names and Dun and Bradstreet (D&B) numbers of parent company and facility locations (U.S. Environmental

[12] Two studies defined the prior reduction in 33/50 releases as the percentage reduction relative to the base year (Arora and Cason, 1996; Khanna and Damon, 1999).
[13] However, Vidovic and Khanna (2007) define prior change in releases such that it is 0 for years 1992-1995, and non-zero for the year 1991, in the second-stage equation.

Protection Agency, 2004). We use the TRI data to create an unbalanced panel of facilities eligible to participate in the 33/50 program if they emitted 33/50 releases over the period 1988-1990. This led to 16,352 eligible facilities in 48 U.S states for the period 1988-1995. Of these eligible facilities, we identified 11,597 facilities for which parent company information was available for the period 1988-1995. Of these, 2,569 facilities had to be dropped from the sample as they were no longer reporting to TRI from 1991 onwards. As a result, our econometric estimation of equation [2-2] includes 9,028 facilities and 35,827 observations. In estimating equation [2-1], we lose some observations due to first differencing and missing lagged variables for some of the observations. Although the panel dataset used for equation (1) is un-balanced, the average length of period for each facility in the data set is 3.89 years; with only 77% of observations remaining in the dataset for at least 3 years. As a result, we are left with 8,756 facilities and 34,339 observations for estimating equation [2-2].

These facilities are identified as belonging to 4,123 parent companies using parent company names and D&B numbers reported in TRI, of which 1,203 parent companies participated in the 33/50 program.[14] We use company names reported in (33/50 Program office, 1991, U.S. Environmental Protection Agency, 1992) to identify the parent companies that were in the first invitation group and use that information to determine the facilities that belonged to these firms. The EPA reports that 517 firms were invited first (in March 1991) to participate in the program. Of these, 328 firms joined the program. Of the 5,400 firms in the second invitation group contacted by the EPA in July 1991, 819 firms joined the program. Subsequently, 140 other firms participated in the program (U.S. Environmental Protection Agency, 1997). We are able to

[14] The EPA listed 1294 parent companies as participants in the 33/50 program in their final report in 1997. We were unable to find 91 of these parent company names in the 2004 release of TRI database (since some company names may have been updated by the EPA).

identify 319 out of the 328 participating companies in the first invitation group; 760 out of 819 participants in the second invitation group and 124 of the 140 remaining participating companies.

We obtain the list of 33/50 participating companies and information about the participation status of each of their facilities through personal communication with Hampshire Research [15]. We found with only 23.6% of the facilities (1335 facilities) belonging to participating parent companies participated in the program, instead of 100% (5595 facilities) assumed by all previous studies. More specifically, the low participation rate at the facility level was driven by the fact that most firms with multiple facilities had only one or a few participating facilities. Therefore assuming that all facilities of all 33/50 companies participated in the program is incorrect when examining the impact of the program on releases[16].

Facility-specific data on the numbers of violations, penalties and inspections for compliance with mandatory air regulations are obtained from EPA's AIRS Facility Subsystem (AFS) database (U.S. Environmental Protection Agency, 2007a). These data were merged with the TRI data using the unique TRI-identifier for each facility. The reported location of a facility in the TRI data-set was used to merge the above data with county's median income from 1990 census and county's attainment status (U.S. Environmental Protection Agency, 2007b) and with state level scores on environmental legislations (League of Conservation Voters, 2007). We use

[15] Facility level participation data was obtained from Catherine Miller, Hampshire Research, www.hampshire.org.
[16] The low participation rate at the facility level for the multi-plants companies could indicate that the incentive for the companies to enroll another facility was significantly reduced once one facility had enrolled. We thank the anonymous reviewer for raising this point. We informally test this idea using a bivariate probit model with a facility's participation decision and the decision to participate by all other facilities as the two discrete choice variables. We find that participation by other facilities had a negative statistically significant impact on a facility's participation decision. We do not present these results here for brevity but they are available from the authors on request.

the Threshold Values Limit[17] as toxicity index to calculate the toxicity weighted 33/50 releases, as in Maxwell et al. (2000) and Sam et al. (2009).

Our data show that total 33/50 releases for our sample facilities dropped by 15.7% between 1988 and 1991 and by 58.7% between 1988 and 1995 (this is close to the estimates reported by the EPA (U.S. Environmental Protection Agency, 1997)). Sum of releases of OD chemicals for our sample declined by 90% while those of non-OD chemicals declined by 53% over the 1988-1995 period. The average releases of toxicity weighted 33/50 releases by program participants declined by 72% and those by non-participants declined by 40% over this period. The average releases of the two OD chemicals by program participants declined by 92% while those by non-participants declined by 84% (Figure 2.1). Over the same period, the average releases of the 15 non-OD chemicals declined by 41% for participating facilities and by 27% for non-participating facilities (Figure 2.2).

2.6 Determinants of Program Participation

Summary statistics for the data used in this study are reported in Tables2.1 and 2.2. Table 2.1 shows that on average participating facilities emit more 33/50 releases, face greater frequency of inspections, and are located in counties with non-attainment status for a larger number of criteria pollutants and in states with higher LCV scores as compared to non-program participants. Table 2.2 shows that about half of our sample comes from chemical, fabricated metal and primary metal industries.

[17] The TLV of a chemical substance is a level to which it is believed a worker can be exposed day after day for a working lifetime without adverse health effects.

Parameter estimates obtained from the pooled probit[18] models on probability of program participation at facility level are shown in Table 2.3. The estimation uses data from 1991-1995 and includes 9,028 facilities and 35,827 observations. We consider three different specifications which include the three instrumental variables in a sequential manner. Model I includes the dummy variable equal to one if the parent company was in the first invitation group. Model II includes the variables in Model I and the facility's share in the parent company's TRI releases as an additional explanatory variable. Model III includes the previous two instrumental variables and the prior change in releases by the parent company of the facility. The AIC decreases from 21,732 in Model I to 20,360 Model III suggesting that Model III provides the best fit to the data.

Although most previous studies have modeled program participation at firm level, our participation models at facility level yield similar results as previous studies in the following aspects[19]: first, facilities belonging to a parent company that were the first invitees were more likely to participate in the program (Arora and Cason, 1996; Gamper-Rabindran, 2006; Khanna and Damon, 1999; Vidovic and Khanna, 2007). Second, facilities belonging to a parent company

[18] To test the robustness of our estimate of the probability of participation, we estimated several alternative specifications of equation [2-2]. Although participation in the program was voluntary and a facility was free to withdraw at any time, in practice, no participating facility withdrew from the program over the 1991-1995 period. To account for that, we estimated a model using data that excluded facilities after the first year in which they participated as in Khanna and Damon (1999). The results of our analysis for equations [2-1] and [2-2] are qualitatively the same as those reported in the paper and are available from the authors on request. Additionally, we also estimated a model that considers a facility's participation decision as being nested within its parent company's participation decision using a bivariate probit model. The two discrete decision variables in this case were a firm's participation decision and the participation decision of a facility within a participating parent firm. The explanatory variables used were the same as those included in Table 2. We obtained the predicted probability of participation for each facility from this model and used that as an instrument in the two-step approach. These parameter estimates for equation [2-1] were found to be similar in magnitude and direction as those reported in Table 2.3 and are available on request from the authors.

[19] Previous studies at firm level also have found that close proximity to consumers is one of the significant determinants in program participation. This effect is usually approximated by a dummy variable indicating a firm is producing final product sold to consumers (Khanna and Damon, 1999; Sam, et al., 2009). We do not find it to be a significant factor in our analysis across all specifications, possibly because facilities have less direct contact with consumers than their parent companies. Thus, we do not report the results including final product variable.

that had achieved greater reductions in 33/50 releases between 1988 and 1990 were more likely to participate (Innes and Sam, 2008). Third, facilities that were inspected more frequently for compliance with clean air regulations were also more likely to participate in the 33/50 program (Innes and Sam, 2008; Sam, et al., 2009)[20]. Like Gamper-Rabindran (2006), we find that the HAP-TRI ratio for a facility is not a statistically significant determinant of program participation in all three specifications[21]. Previous studies have found mixed evidence on the effect of county characteristics (percentage of poverty, and minority population in the county) on program participation (Gamper-Rabindran, 2006). Our results show that facilities located in non-attainment counties and in counties with higher median household income were more likely to participate in the program. Facilities located in a state with better scores on environmental bills were more likely to participate in the program. Additionally, by analyzing facility participation we find that facilities accounting for a larger share of parent company TRI emissions were more likely to participate. We use the predicted probability from Model III as an instrument in the following estimations reported in Table 2.3 to Table 2.7.

2.7 Impact of 33/50 Program on Releases

We report the feasible efficient GMM estimates that are robust to heteroskedasticity and clustering, the number of over identified conditions, the associated P values for the Hansen's J test statistics of over identification and the Kleibergen-Paap rk statistics for weak identification (Baum, et al., 2003) in Table 2.4-2.7.

[20] In contrast to previous studies at firm level, we do not include lagged 33/50 releases, TRI releases or 33/50-TRI ratio at the facility level in our program participation model because of possible serial correlation among the unobservable factors influencing participation and toxic release levels.

[21] They find an exception to this in the case of the chemical industry.

The test statistics on over identification[22] are not statistically significant at the 5% level in all models except Column XII and Column XVI, indicating the validity of our instruments. The reason for the significant test statistic for over-identification in Column XII and Column XVI of Table 2.6 and Table 2.7 is mostly likely due to the small sample resulting from the fact that the releases of OD chemicals were almost completely phased out in the later period of the program, and the sample of facilities reporting OD chemicals declined significantly over time[23]. We also test for auto-correlation of the errors of the models estimated in Tables 2.4 to 2.7. As expected, first-order autocorrelation does exist due to first-differencing of equation [2-1]. However, second-order autocorrelation is rejected for all models, using tests suggested in (Wooldridge, 2002) p.282-283).

2.7.1. Main Results

Our results are as follows. We find that program participants reduced 33/50 releases statistically significantly more than non-participants. All models in Table 2.4 show that the program's effect on the change of 33/50 releases is negative and significant (Table 2.4, row 2). Model IV includes the prior change in 33/50 releases as an explanatory variable and uses y_{it-2} as instrument. Model V has the same explanatory variables as Model IV but uses 33/50 releases in 1988 and 1989 as instruments[24]. Model VI has the same instruments as Model IV but excludes the prior change in 33/50 releases as an explanatory variable. Model VII includes the same explanatory variables as Model VI but uses 33/50 releases in 1988 and 1989 as instruments.

[22] The validity of the entire set of instruments can be tested by Hansen's J statistic that measures the value of GMM criterion function at the efficient GMM estimator under the null. It follows a chi-squared distribution with degrees of freedom equal to the number of over identifying restrictions under the null (Baum, et al., 2007).

[23] The test has lower power in small sample cases and rejects orthogonality too often in small samples (Hansen, et al., 1996, Hayashi, 2000).

[24] We estimated the models in Table 2.4 and Table 2.5 using the corresponding 1988 and 1989 33/50 releases as instruments. Because those results differ little from results currently reported in Table 4 and 5 we do not include them in the tables. They are available upon request.

Across the four specifications, the coefficient of the 33/50 participation variable ranges from -0.237 to -0.188. Since the 33/50 releases are included in logarithm form, the coefficient on program participation measures the difference in the rate of reduction between participants and non-participants. In other words, the rate of reduction of 33/50 releases for participants was 18.8% to 23.7% higher than for non-participants.

Contrary to the conclusion of Vidovic and Khanna (2007), we find the program's effect to be negative and statistically significant even after including the prior change of 33/50 releases as an explanatory variable in the second step estimation (Model IV and V). Furthermore, across the four columns in Table 2.4, we find that facilities with a higher HAP-TRI ratio in the previous period achieved greater reduction in 33/50 releases (Table 2.4, row 4). Facilities that are located in counties with higher median income experienced greater reduction of 33/50 releases. Since both releases and county median income are measured in logarithm, we conclude that a 1 percent increase in county median income resulted in 0.07% to 0.08% increase in the rate of reduction (Table 2.4, row 9),

2.7.2. Alternative Specifications

Our main specifications in Table 2.4 include the lagged dependent variable and the results indicate that the lagged change in 33/50 releases is strongly correlated with the current change in releases and that change in 33/50 releases is a continuous process. The positive coefficients on the time dummies indicates that there was also a discrete downward trend in 33/50 releases even in the absence of the program, though the rate of reduction diminished over time. To check that our results are robust to the inclusion of the lagged dependent variable, we also estimated the specification (Model VIII) in Table 2.5 without this variable. We find that program participation continues to have a statistically significant negative impact on 33/50

releases although the coefficient for program participation becoming much larger than in previous specifications. The statistical significance of the lagged dependent variable in earlier models indicates path dependency in emissions. This suggests the potential for omitted variable bias in this specification and that greater reliance should be placed on the program effect obtained from those specifications.

Furthermore, it is possible that the effect of the 33/50 program was not continuous over the duration of the program; instead program participants could have adopted abatement methods that led to discrete reductions in their 33/50 releases[25]. If this was the case, the effect of the program might differ over the course of the program, with abatement in initial years raising the marginal abatement cost and reducing incentives to reduce emissions in later years of the program. The results with the inclusion of a time-specific participation variable are presented in Model IX in Table 2.5. We create these time-specific participation variables (participation 1991 to participation 1997) for each year of the program as in Innes and Sam (2008)[26]. The coefficient

[25] We thank the anonymous reviewer for raising this point.

[26] We first create new dummy variables as $D_{it} = 1$, if facility i participated in the program in year t, and zero otherwise. We then constructed new program participation variables for each year (part1991, part1995), such that $Part_s = \sum_{t=s}^{1995} D_{it}$, for $s = 1991,1992,...1995$.For example, for a facility that participated from 1991 onwards, this results in a vector of new participation variables such as $part' = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 1 & 1 & 0 & 0 & 0 \\ 1 & 1 & 1 & 0 & 0 \\ 1 & 1 & 1 & 1 & 0 \\ 1 & 1 & 1 & 1 & 1 \end{bmatrix}$

We obtain the predicted probability $\hat{P}$ from the first stage participation model and create the vector of instrumental variables IV' for the new participation variables such as

of each of these time specific participation variable represents the incremental effect of participation on 33/50 releases that year. For example, the coefficient of participation1992 measures the effect of the 33/50 program on change in releases from 1992 onwards. Lastly, we also examine if the program had an effect on emissions after it ended in 1995. In Model X we include time specific participation dummies for 1996 and 1997 in addition to previous year.

We find that the effect of the program on 33/50 releases remains robust to these alternative specifications and that the program still had a significant and negative impact on the change of 33/50 releases. However, we now observe that the program's effect was most evident in 1992 (Table 2.5, Row 3). This is consistent with Innes and Sam (2008) who also measure the program's effect from 1992 to 1995 and find it to be negative and statistically significant only in 1992. Contrary to Sam et al. (2009) that find a significant and negative impact of the 33/50 program for the period of 1996-1998, we find that the program did not have additional significant impacts after the program ended.

2.7.3. Toxicity –weighted Releases and Regulation on OD Chemicals

We now examine the program's effect on toxicity-weighted 33/50 releases, on OD chemicals and the rest of 33/50 chemicals. Model XI in Table 2.6 (using y_{it-2} as instrument) shows that the program had a statistically significant negative impact on the toxicity weighted sum of 33/50 releases. The rate of reduction for program participants is 32.2% higher than for non-participants, even after we control for the effect of prior reduction in 33/50 releases. These

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$$IV' = \begin{bmatrix} \widehat{P} & 0 & 0 & 0 & 0 \\ \widehat{P} & \widehat{P} & 0 & 0 & 0 \\ \widehat{P} & \widehat{P} & \widehat{P} & 0 & 0 \\ \widehat{P} & \widehat{P} & \widehat{P} & \widehat{P} & 0 \\ \widehat{P} & \widehat{P} & \widehat{P} & \widehat{P} & \widehat{P} \end{bmatrix}$$

The analysis for period 1991-1997 follows the same strategy with program participants in 1995 represented as participants in years 1996 and 1997

results indicate that program participants reduced both the total amount of 33/50 releases and toxicity weighted 33/50 releases. We do not find county median income to have a significant effect on the change in toxicity weighted 33/50 releases (Table 2.6, Row9). Gamper-Rabindran (2006) also finds that these environmental justice indicators such as education level and poverty did not have a statistically significant effect on toxicity-weighted releases; instead facilities in counties with higher voter's participation ratio experienced greater reduction in toxicity-weighted releases.

Additionally, we find that the program's effect varied by groups of chemicals. Model XII (Table 2.6) examines the program's impact of OD chemicals and shows that the effect of the program on OD chemicals was not statistically significant. This suggests that since OD chemicals were supposed to be phased out by 1996, all facilities had incentives to reduce their dependence on those two chemicals and that these reductions were not induced by the 33/50 program. In contrast, the program's effect on non-OD releases is negative and statistically significant as reported in Model XIII, Table 2.6. The annual rate of reduction of non-OD 33/50 releases is 20.8% higher for participants than non-participants. The overall reduction in 33/50 releases was, therefore, not solely due to the mandatory phase-out of OD chemicals.

Since the Montreal Protocol was first signed in 1987, facilities might have taken measures to reduce their OD chemicals even in the absence of the voluntary 33/50 program. To further investigate the relative effectiveness of the voluntary 33/50 program vs. the mandatory regulations for OD chemicals, we include the percentage of OD releases in total 33/50 releases before the program started as an explanatory variable (Table 2.6, Model XIV). Firms with a larger value of this variable are more likely to have felt the stringency of the Montreal Protocol and could have made greater efforts to reduce OD releases and thus their 33/50 releases. We find

this variable does have a negative and statistically significant effect on 33/50 releases but the sign and even the magnitude of the effect of the 33/50 program are unchanged. The reduction in 33/50 releases appears to have been largely due to the voluntary 33/50 program instead of the OD regulation whose effect on 33/50 releases was rather small. Specifically, we find that a 10 percent increase in OD-33/50 ratio led to 0.02% greater rate of reduction in 33/50 releases (Row 3, Model XIV).

2.7.4. Effect of Assuming Participation by All Facilities of 33/50 Parent Companies

In Table 2.7, we compare our results using facility level participation data with those we would have obtained if we had incorrectly attributed participation status to all facilities belonging to a firm from which even one facility had participated. Models XV, XVI and XVII use with the same instrument set as in Model IV but are estimated assuming that all facilities in a firm participated even if only one facility had participated. We find that, in this case, the program's effect on overall 33/50 releases is attenuated to - 5.1% in Model XV for all 33/50 chemicals and -6.6% in Model XVII for non-OD chemicals.

Finally, our estimates show that the impact of program participation on the expected levels of 33/50 releases is greater than the estimates by Khanna and Damon (1999) and the estimates by Innes and Sam (2008). Since our estimated coefficient $\hat{\theta}$ on program participation represents the effect of the program on the rate of reduction in releases, we derive the program's impact on the levels of releases, in order to compare our estimates with those of previous studies. We also include the dynamic effect of program-induced previous reductions in 33/50 releases on current releases. Estimates obtained using the coefficients of two specific Models (XIV and IX) are shown in Table 2.8. Estimates derived from using the coefficients of other models estimated

in Table 3 yield very similar results. Our findings for the 1991-1995 period for all participating facilities imply that the percentage decrease due to program was about 44% to 56% compared to the average 33/50 releases of the participants in 1990 (Row 6, Table 2.8). Compared to the sample average 33/50 releases in 1990, Khanna and Damon (1999) estimate that the percentage decrease due to program was about 27.92 % over the period 1991 -1993 for the chemical industry. Focusing only on the average 33/50 releases of the participants, Innes and Sam (2008) estimated the reduction in 33/50 releases (relative to the 1990 level) that could be attributed to the program to be more than 45%, over the period of 1992-1995. In addition, Innes and Sam (2008) find that 70%-85% of the total reduction occurred in the first year of the program, 1992. We find that the reduction in 1992 was the largest compared to the rest of the years but it accounted for 36% of the total reduction[27]

2.8 Conclusions

This study reassesses the effectiveness of the 33/50 program using facility level participation and emissions data for all eligible facilities reporting to TRI for the 1988-1995 period. It examines the extent to which the program induced reductions in releases over and above those that would have been achieved otherwise, or simply due to regulations to phase out the OD chemicals and whether the program impact differed across chemical types. We use Arellano and Bond's (1991) GMM approach with valid instrumental variables which enables us to control for endogeneity associated with program participation and dynamics of emissions production. This method is applied using the largest possible sample of over 8,000 facilities eligible for participation in the 33/50 program for which data was available.

[27] Innes and Sam (2008) assume that all participants participated in 1992 due to data availability. We include additional time-specific participation information in our estimates. Our data show that that 40% of the participants enrolled in the program after 1992 instead of 100% assumed by Innes and Sam (2008). This could explain the difference between our results and Innes and Sam (2008).

Our results show that 33/50 facilities significantly reduced their overall 33/50 releases. Across various specifications, the rate of reduction in 33/50 releases for program participants is 14.8% to 23.7% higher than non-participants, after controlling for industry effects, time trend and other regulatory pressures. The program had a statistically significant impact on releases of the 15 non-OD chemicals but not on the OD chemicals. Reductions in releases of OD chemicals appear to have been motivated primarily by the Montreal Protocol. However, the overall impact of the Montreal Protocol on 33/50 releases was relatively small compared to the effect of the 33/50 program, indicating the importance of voluntary programs in expanding the reach of existing mandatory regulations.

Furthermore, we find that the program's incremental effect was statistically significant at the beginning of the program and did not continue beyond the duration of the program. The assessment of program outcomes obtained by using facility-specific participation information differs considerably from that obtained by incorrectly assuming that all facilities of a parent company participated in the program if even one facility participated.

In conclusion, this paper provides a more accurate assessment on the effectives of 33/50 program by using facility level participation information as compared to previous studies. It shows the importance of having accurate data and of undertaking analysis at a disaggregated scale since program participation impacts differ across facilities within a parent company and across the program chemicals that were affected differentially by regulatory pressures. This paper examined the average effect of the 33/50 program across all industries. The effects of participation could differ across industries for various reasons, including differences in the technological possibilities for abatement, costs of abatement, the stringency of the regulatory threats faced by the industry and changes in demand conditions. Previous studies by Gamper-

Rabindran (2006) and Vidovic and Khanna(2007) provide mixed evidence of this. Further research using facility specific participation information is needed to examine the extent to which the program led to differential effects across industries and to explain its causes.

2.9 Tables and Figures

Table 2.1 Summary Statistics, 1991-1995.

	All Facilities	33/50 facilities	Non-33/50 facilities
Facility level variables	**Mean**	**Mean**	**Mean**
33/50 releases (1000 pounds)	84.20	110.68	80.41
	(296.57)	(370.43)	(284.25)
OD releases(1000 pounds)	8.18	12.04	7.63
	(44.02)	(58.51)	(41.50)
Non-OD releases(1000 pounds)	76.02	98.63	72.78
	(291.18)	(366.36)	(278.62)
HAP/TRI ratio(Percentage)	75.79	75.26	75.87
	(31.41)	(31.24)	(31.43)
Number of inspections (AFS)	0.42	0.48	0.41
	(1.16)	(1.25)	(1.14)
Control variables			
County non-attainment status	0.99	1.17	0.97
	(1.15)	(1.16)	(1.15)
LCV score	97.19	101.63	96.56
	(39.10)	(36.87)	(39.37)
Number of facilities	8756	1085	7671
Total observations	34339	4299	30040

Standard errors in parentheses

Table 2.2 Sample Distribution by Industry, 1991-1995.

Industry	Percentage in sample	Percentage of 33/50 facilities
SIC 26: Paper	3.40	3.65
SIC 28: Chemical	18.24	22.66
SIC 29: Petroleum	2.59	2.14
SIC 30: Rubber	7.41	5.21
SIC 33: Primary metal	10.73	12.63
SIC 34: Fabricated metal	14.86	15.75
SIC 35: Machinery & computer	7.26	3.47
SIC 36:Electronics	7.94	7.89
SIC 37:Transportation	9.28	10.70
SIC 38: Instruments	2.07	1.28
Other Manufacture industries	16.23	14.63

Table 2.3 Determinants of Program Participation at Facility Level , 1991-1995.

Variables	I Program participation	II Program participation	III Program participation
First Invitation Group	0.245***	0.567***	0.473***
	[0.037]	[0.046]	[0.051]
Share in total TRI releases of parent company		0.814***	0.891***
		[0.052]	[0.054]
Firm prior change in releases			-0.121***
			[0.019]
HAP-TRI ratio	0	0	0
	[0.001]	[0.001]	[0.001]
Number of inspections	0.030**	0.023*	0.016
	[0.014]	[0.014]	[0.014]
SIC 26: Paper	0.092	0.133	0.143
	[0.107]	[0.108]	[0.110]
SIC 28: Chemical	0.185***	0.247***	0.238***
	[0.063]	[0.063]	[0.065]
SIC 29: Petroleum	-0.123	-0.063	-0.076
	[0.132]	[0.136]	[0.138]
SIC 30: Rubber	-0.191**	-0.154*	-0.123
	[0.084]	[0.084]	[0.085]
SIC 33: Primary metal	0.169**	0.208***	0.228***
	[0.073]	[0.076]	[0.076]
SIC 34: Fabricated metal	0.069	0.09	0.089
	[0.064]	[0.065]	[0.066]
SIC 35: Machinery & computer	-0.378***	-0.307***	-0.332***
	[0.095]	[0.097]	[0.097]
SIC 36:Electronics	0.033	0.089	0.06
	[0.078]	[0.079]	[0.080]
SIC 37:Transportation	0.147**	0.251***	0.128*
	[0.073]	[0.075]	[0.075]
SIC 38: Instruments	-0.290**	-0.265*	-0.309**
	[0.146]	[0.149]	[0.154]
County non-attainment status	0.034**	0.031*	0.033*
	[0.017]	[0.017]	[0.018]

Table 2.3 (Cont.)

Variables	I Program participation	II Program participation	III Program participation
State LCV scores	0.869***	0.926***	0.846***
	[0.195]	[0.199]	[0.201]
State LCV scores squared	-0.411***	-0.447***	-0.414***
	[0.095]	[0.097]	[0.098]
Year 1992	0.428***	0.429***	0.441***
	[0.020]	[0.020]	[0.021]
Year 1993	0.496***	0.502***	0.519***
	[0.022]	[0.023]	[0.023]
Year 1994	0.542***	0.549***	0.566***
	[0.023]	[0.024]	[0.025]
Year 1995	0.585***	0.591***	0.602***
	[0.026]	[0.027]	[0.027]
County median income	0.293***	0.278***	0.268***
	[0.092]	[0.094]	[0.095]
Constant	-5.307***	-5.659***	-5.603***
	[0.936]	[0.962]	[0.970]
Observations	35827	35827	35827
AIC	21732.57	20717.67	20360.07
Correctly Classified	90.36%	90.37%	90.24%

Note: We use pooled probit models to estimate Model I to Model III. Robust standard errors in brackets (clustered by facility). The predicted probabilities in Model III are used in all the following estimates. *** p<0.01, ** p<0.05, * p<0.1.

Table 2.4 Program's Effect on 33/50 Releases, 1991-1995.

Variables	IV 33/50 releases	V 33/50 releases	VI 33/50 releases	V II 33/50 releases
Lagged releases	0.484***	0.515***	0.486***	0.518***
	[0.029]	[0.052]	[0.029]	[0.052]
Program participation	-0.225**	-0.237**	-0.188**	-0.195**
	[0.092]	[0.094]	[0.081]	[0.083]
Firm prior change in releases	-0.004	-0.005		
	[0.005]	[0.005]		
HAP-TRI ratio	-0.009***	-0.009***	-0.009***	-0.009***
	[0.001]	[0.001]	[0.001]	[0.001]
Number of inspections	-0.007	-0.006	-0.007	-0.006
	[0.011]	[0.011]	[0.011]	[0.011]
State LCV scores	0.294*	0.350**	0.292*	0.348**
	[0.177]	[0.174]	[0.177]	[0.174]
State LCV scores squared	-0.118	-0.142*	-0.117	-0.141*
	[0.086]	[0.085]	[0.086]	[0.085]
County non-attainment status	0.035	0.03	0.035	0.03
	[0.031]	[0.030]	[0.031]	[0.030]
County median income	-0.082***	-0.076***	-0.084***	-0.077***
	[0.027]	[0.027]	[0.027]	[0.027]
Year 1991	0.604**	0.543*	0.622**	0.559**
	[0.277]	[0.278]	[0.277]	[0.277]
Year 1992	0.778***	0.708**	0.794***	0.722***
	[0.276]	[0.278]	[0.275]	[0.277]
Year 1993	0.676**	0.615**	0.691**	0.628**
	[0.276]	[0.278]	[0.275]	[0.278]
Year 1994	0.793***	0.732***	0.807***	0.745***
	[0.275]	[0.277]	[0.275]	[0.277]
Year 1995	0.708**	0.649**	0.723***	0.661**
	[0.276]	[0.278]	[0.275]	[0.278]
SIC 26: Paper	0.033	0.034	0.033	0.034
	[0.027]	[0.027]	[0.027]	[0.027]
SIC 28: Chemical	0.060***	0.060***	0.060***	0.060***
	[0.020]	[0.020]	[0.020]	[0.019]
SIC 29: Petroleum	0.039	0.039	0.041	0.041
	[0.030]	[0.031]	[0.030]	[0.030]

Table 2.4 (Cont.)

Variables	IV 33/50 releases	V 33/50 releases	VI 33/50 releases	V II 33/50 releases
SIC 30: Rubber	0.014	0.012	0.013	0.011
	[0.024]	[0.024]	[0.024]	[0.024]
SIC 33: Primary metal	0.017	0.018	0.015	0.016
	[0.025]	[0.025]	[0.025]	[0.025]
SIC 34: Fabricated metal	-0.003	0	-0.003	0
	[0.023]	[0.023]	[0.023]	[0.023]
SIC 35: Machinery & computer	-0.078**	-0.077**	-0.075**	-0.074**
	[0.030]	[0.031]	[0.030]	[0.030]
SIC 36:Electronics	-0.116***	-0.109***	-0.115***	-0.108***
	[0.027]	[0.028]	[0.027]	[0.028]
SIC 37:Transportation	-0.009	-0.007	-0.006	-0.003
	[0.023]	[0.024]	[0.023]	[0.023]
SIC 38: Instruments	-0.104**	-0.106**	-0.101**	-0.102**
	[0.049]	[0.049]	[0.048]	[0.048]
Observations	34339	34339	34339	34339
R-squared	-0.349	-0.386	-0.35	-0.39
Number of over identified conditions	4	9	4	9
Over identification test(P-value)	0.0917*	0.159	0.0914*	0.151
Weak Identification test	61.48***	34.73***	81.39***	35.28***
Number of facilities	8756	8756	8756	8756

Note: Model IV uses yit-2 and the predicted probability of Model III as instruments. Model V uses facility's releases in 1988 and 1989 as instruments in addition to the predicted probability. Model VI uses the same instruments as Model IV but excludes the firm's prior change in 33/50 releases as an explanatory variable. Model VII uses the same instruments as Model V but excludes the firm's prior change in 33/50 releases as an explanatory variable. Robust standard errors in brackets (clustered by facility). *** p<0.01, ** p<0.05, * p<0.1.

Table 2.5. Alternative Specifications Evaluating the Program's Effect, 1991-1997.

Variables	VIII 33/50 releases	IX 33/50 releases	X 33/50 releases
Lagged 33/50 releases		0.492***	0.517***
		(0.028)	(0.025)
Program participation(1991-1995)	-0.318***		
	(0.091)		
Participation 1991		-0.04	0.001
		(0.040)	(0.033)
Participation 1992		-0.148**	-0.158***
		(0.064)	(0.058)
Participation 1993		0.105	0.112
		(0.097)	(0.089)
Participation 1994		-0.002	-0.008
		(0.103)	(0.100)
Participation 1995		-0.053	-0.076
		(0.107)	(0.108)
Participation 1996			0.21
			(0.150)
Participation 1997			-0.079
			(0.144)
HAP-TRI ratio	-0.002***	-0.009***	-0.011***
	(0.001)	(0.001)	(0.001)
Number of inspections	-0.007	-0.008	-0.008
	(0.009)	(0.011)	(0.008)
State LCV scores	0.332**	0.292	0.281*
	(0.149)	(0.178)	(0.166)
State LCV scores squared	-0.145**	-0.117	-0.114
	(0.073)	(0.087)	(0.081)
County non-attainment status	0.03	0.034	0.006
	(0.027)	(0.031)	(0.028)
County median income	-0.135***	-0.089***	-0.058***
	(0.029)	(0.027)	(0.021)
Year 1991	1.108***	0.670**	0.356
	(0.302)	(0.274)	(0.221)
Year 1992	1.258***	0.849***	0.515**
	(0.301)	(0.273)	(0.219)

Table 2.5 (Cont.)

Variables	VIII 33/50 releases	IX 33/50 releases	X 33/50 releases
Year 1993	1.199***	0.730***	0.408*
	(0.301	(0.274)	(0.218)
Year 1994	1.292***	0.846***	0.522**
	(0.3)	(0.273)	(0.218)
Year 1995	1.186***	0.768***	0.457**
	(0.301)	(0.274)	(0.219)
Year 1996			0.457**
			(0.219)
Year 1997			0.509**
			(0.219)
Industry effects	Included	Included	Included
Observations	34339	34339	44922
Number of over identified conditions	0	4	6
Over identification test(P-value)	--	0.09*	0.05*
Weak Identification test	265***	86.17***	73***
Number of facilities	8756	8756	8834

Note: All models estimated include the ten industry dummy variables. Model VIII uses the same instruments for participation as Model VI but excludes the lagged dependent variable. Model IX and Model X uses the same instruments for the lagged dependent variables as Model VI . However, the instruments for time-specific participation variables are created in the following way. We first create new dummy variables as $D_{it} = 1$, if facility i participated in the program in year t, and zero otherwise. We then constructed new program participation variables for each year (part1991, part1995), such that $Part_s = \sum_{t=s}^{1995} D_{it}$, for $s = 1991,1992,...1995$ .For example, for a facility that participated from 1991 onwards, this results in a vector of new participation variables such as

$$part' = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 1 & 1 & 0 & 0 & 0 \\ 1 & 1 & 1 & 0 & 0 \\ 1 & 1 & 1 & 1 & 0 \\ 1 & 1 & 1 & 1 & 1 \end{bmatrix}$$

. We obtain the predicted probability $\hat{P}$ from the first stage participation model and create the vector of instrumental variables IV' for the new participation variables such as

$$IV' = \begin{bmatrix} \hat{P} & 0 & 0 & 0 & 0 \\ \hat{P} & \hat{P} & 0 & 0 & 0 \\ \hat{P} & \hat{P} & \hat{P} & 0 & 0 \\ \hat{P} & \hat{P} & \hat{P} & \hat{P} & 0 \\ \hat{P} & \hat{P} & \hat{P} & \hat{P} & \hat{P} \end{bmatrix}$$

The analysis for period 1991-1997 follows the same strategy with program participants in 1995 represented as participants in years 1996 and 1997 . Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 2.6. Program's Effect on Toxicity Weighted 33/50 Releases and Two Groups of Chemicals, 1991-1995.

Variables	XI Toxicity-weighted	XII OD releases	XIII Other 15 Chemicals	XIV 33/50 releases
Lagged releases	0.657***	0.890***	0.408***	0.469***
	(0.032)	(0.018)	(0.034)	(0.029)
Program participation	-0.322**	-0.039	-0.208**	-0.203**
	(0.138)	(0.107)	(0.106)	(0.092)
OD-33/50 ratio in 1988				-0.002***
				(0.000)
HAP-TRI ratio	-0.015***	0	0.002	-0.009***
	(0.002)	(0.007)	(0.006)	(0.001)
Firm prior change in releases	0.003	-0.005***	-0.007***	-0.004
	(0.008)	(0.001)	(0.001)	(0.005)
Number of inspections	-0.011	-0.003	0.002	-0.007
	(0.020)	(0.027)	(0.012)	(0.011)
State LCV scores	0.409	-0.029	0.165	0.284
	(0.302)	(0.258)	(0.197)	(0.176)
State LCV scores squared	-0.175	-0.015	-0.083	-0.112
	(0.146)	(0.126)	(0.097)	(0.086)
County non-attainment status	0.067	0.065	0.045	0.041
	(0.049)	(0.046)	(0.039)	(0.030)
County median income	-0.057	-0.031	-0.061*	-0.058**
	(0.041)	(0.030)	(0.031)	(0.027)
Year 1991	0.325	0.15	0.372	0.383
	(0.416)	(0.305)	(0.321)	(0.276)
Year 1992	0.521	0.269	0.557*	0.552**
	(0.414)	(0.303)	(0.321)	(0.275)
Year 1993	0.364	0.196	0.703**	0.446
	(0.414)	(0.301)	(0.320)	(0.275)
Year 1994	0.586	0.349	0.611*	0.559**
	(0.413)	(0.301)	(0.320)	(0.275)
Year 1995	0.53	0.388	0.457	0.472*
	(0.413)	(0.302)	(0.321)	(0.275)

Table 2.6 (Cont.)

Variables	XI Toxicity-weighted	XII OD releases	XIII Other 15 Chemicals	XIV 33/50 releases
SIC 26: Paper	0.044	0.022	-0.006	0.022
	(0.035)	(0.038)	(0.033)	(0.027)
SIC 28: Chemical	0.046*	0.015	0.004	0.055***
	(0.027)	(0.021)	(0.021)	(0.020)
SIC 29: Petroleum	0.021	-0.119***	-0.003	0.029
	(0.045)	(0.046)	(0.032)	(0.030)
SIC 30: Rubber	-0.038	-0.122***	0.006	0.029
	(0.034)	(0.036)	(0.034)	(0.024)
SIC 33: Primary metal	-0.081**	-0.024	0.044	0.025
	(0.037)	(0.027)	(0.028)	(0.025)
SIC 34: Fabricated metal	-0.095***	-0.111***	0.059**	0.008
	(0.035)	(0.026)	(0.026)	(0.023)
SIC 35: Machinery & computer	-0.181***	-0.059	-0.035	-0.048
	(0.048)	(0.037)	(0.037)	(0.030)
SIC 36:Electronics	-0.193***	-0.099***	-0.082**	-0.088***
	(0.043)	(0.034)	(0.034)	(0.027)
SIC 37:Transportation	-0.075**	-0.157***	-0.019	0.023
	(0.037)	(0.035)	(0.030)	(0.024)
SIC 38: Instruments	-0.237***	-0.267***	0.080*	-0.05
	(0.084)	(0.069)	(0.048)	(0.048)
Observations	34,339	34,339	34,339	34,339
Number of over identified conditions	4	4	4	4
Over identification test(P-value)	0.06*	0***	0.3	0.09*
Weak Identification test	80.56***	47.69***	78.71***	63.51***
Number of facilities	8756	8756	8756	8756

Note: All models estimated use y_{it-2} as instruments for the lagged dependent variables and the predicted probability of Model III as instrument for the participation variable. Robust standard errors in parentheses (clustered by facility). *** p<0.01, ** p<0.05, * p<0.1.

Table 2.7 Evaluation of the Program's Effect Assuming All Facilities of 33/50 Parent Companies Had Participated in the Program, 1991-1995.

Variables	XV 33/50 releases	XVI OD releases	XVII Other 15 Chemicals
Lagged releases	0.493***	0.960***	0.415***
	(0.028)	(0.040)	(0.033)
Program participation	-0.051**	-0.03	-0.066**
	(0.025)	(0.031)	(0.030)
HAP-TRI ratio	-0.004	-0.004	0
	(0.005)	(0.007)	(0.006)
Firm prior change in releases	-0.009***	-0.006***	-0.007***
	(0.001)	(0.001)	(0.001)
Number of inspections	-0.007	-0.009	0.002
	(0.011)	(0.030)	(0.012)
State LCV scores	0.286	-0.001	0.159
	(0.178)	(0.003)	(0.198)
State LCV scores squared	-0.114	0	-0.08
	(0.087)	(0.000)	(0.097)
County non-attainment status	0.035	0.07	0.045
	(0.031)	(0.051)	(0.039)
County median income	-0.092***	-0.015	-0.069**
	(0.027)	(0.030)	(0.031)
Year 1991	0.706**	-0.004	0.461
	(0.274)	(0.309)	(0.318)
Year 1992	0.876***	0.121	0.645**
	(0.273)	(0.308)	(0.318)
Year 1993	0.773***	-0.165	0.791**
	(0.273)	(0.306)	(0.318)
Year 1994	0.890***	0.153	0.698**
	(0.273)	(0.308)	(0.318)
Year 1995	0.805***	0.486	0.545*
	(0.273)	(0.306)	(0.319)
SIC 26: Paper	0.038	0.043	0.003
	(0.027)	(0.041)	(0.033)
SIC 28: Chemical	0.063***	0.027	0.01
	(0.020)	(0.023)	(0.022)

Table 2.7 (Cont.)

Variables	XV 33/50 releases	XVI OD releases	XVII Other 15 Chemicals
SIC 29: Petroleum	0.051*	-0.099*	0.011
	(0.030)	(0.050)	(0.032)
SIC 30: Rubber	0.019	-0.081**	0.01
	(0.024)	(0.038)	(0.033)
SIC 33: Primary metal	0.011	0.001	0.039
	(0.025)	(0.028)	(0.027)
SIC 34: Fabricated metal	-0.004	-0.102***	0.058**
	(0.023)	(0.028)	(0.026)
SIC 35: Machinery & computer	-0.063**	-0.025	-0.021
	(0.030)	(0.040)	(0.036)
SIC 36:Electronics	-0.111***	-0.069*	-0.076**
	(0.027)	(0.037)	(0.034)
SIC 37:Transportation	-0.008	-0.097**	-0.017
	(0.024)	(0.038)	(0.030)
SIC 38: Instruments	-0.091*	-0.206***	0.091*
	(0.048)	(0.072)	(0.047)
Observations	34,339	34339	34,339
Number of over identified conditions	4	4	4
Over identification test(P-value)	0.0901*	0***	0.249
Weak Identification test	140.8	324.1	110.3
Number of facilities	8756	8756	8756

Note: To estimate Model XV to XVII, we assume all facilities belonging to 33/50 parent companies participated in the program. With this assumption, we use Model III to predict a new set of participation probabilities. We use those and y_{it-2} as instruments. Robust standard errors in parentheses (clustered by facility). *** p<0.01, ** p<0.05, * p<0.1

Table 2.8. Impact of Program Participation on the Average 33/50 Releases.

	Based on Model XIV-Table 5		Based on Model IX-Table 4	
Year	**Average decrease in 33/50 releases due to program** (thousand pounds) (A)**	**Percentage reduction due to program (A)/(B)**	**Average decrease in 33/50 releases due to program** (thousand pounds) (C)**	**Percentage reduction due to program (C)/(B)**
1991	-21.27	-14%	-1.05	-1%
1992	-26.65	-17%	-24.51	-16%
1993	-16.91	-11%	-17.31	-11%
1994	-12.27	-8%	-13.58	-9%
1995	-9.58	-6%	-11.35	-7%
1991-1995 total	**-86.68**	**-56%**	**-66.74**	**-44%**
Participants' average 33/50 releases in 1990(thousand pounds) (B)	155.4			

**Note: The coefficient $\hat{\theta}$ on program participation can be approximately viewed as $\hat{\theta} = \dfrac{\partial \dfrac{(y_{it} - y_{it-1})}{y_{it-1}}}{\partial P_{it}}$

where y_{it}, y_{it-1} denote the levels of releases. Since this coefficient represents the additional percentage change in releases due to program participation, we can derive the reduction due to program participation for the participants. We set the initial level of 33/50 releases at the level in 1990; the direct impact due to participation in year t is $\hat{\theta} * \tilde{y}_{it}$ and the indirect impact of the program through a reduction in last year's releases is $\hat{\theta} * \rho^{(t-1991)}$, holding other variables constant. Over time the indirect impact diminishes. We derive the impact due to participation $\Delta\tilde{y}_{t,i}$ for facility i for each year iteratively using the following equations. We take the expectation on those predicted reductions from the samples to get the average decrease due to program per year.

$$\Delta\tilde{y}_{1991,i} = y_{1990,i}(\hat{\theta})$$

$$\Delta\tilde{y}_{1992,i} = \tilde{y}_{1991,i}(\hat{\theta} + \hat{\theta}\rho^{(t-1991)}), \quad \tilde{y}_{1991,i} = y_{1990,i} + \Delta\tilde{y}_{1991,i}$$

$$\Delta\tilde{y}_{1993,i} = \tilde{y}_{1992,i}(\hat{\theta} + \hat{\theta}\rho^{(t-1991)}), \quad \tilde{y}_{1992,i} = y_{1990,i} + \Delta\tilde{y}_{1991,i} + \Delta\tilde{y}_{1992,i}$$

$$\Delta\tilde{y}_{1994,i} = \tilde{y}_{1993,i}(\hat{\theta} + \hat{\theta}\rho^{(t-1991)}), \quad \tilde{y}_{1993,i} = y_{1990,i} + \Delta\tilde{y}_{1991,i} + \Delta\tilde{y}_{1992,i} + \Delta\tilde{y}_{1993,i}$$

$$\Delta\tilde{y}_{1995,i} = \tilde{y}_{1994,i}(\hat{\theta} + \hat{\theta}\rho^{(t-1991)}), \quad \tilde{y}_{1994,i} = y_{1990,i} + \Delta\tilde{y}_{1991,i} + \Delta\tilde{y}_{1992,i} + \Delta\tilde{y}_{1993,i} + \Delta\tilde{y}_{1994,i} + \Delta\tilde{y}_{1995,i}$$

Figure 2.1 Average OD Releases, 1988-1995.

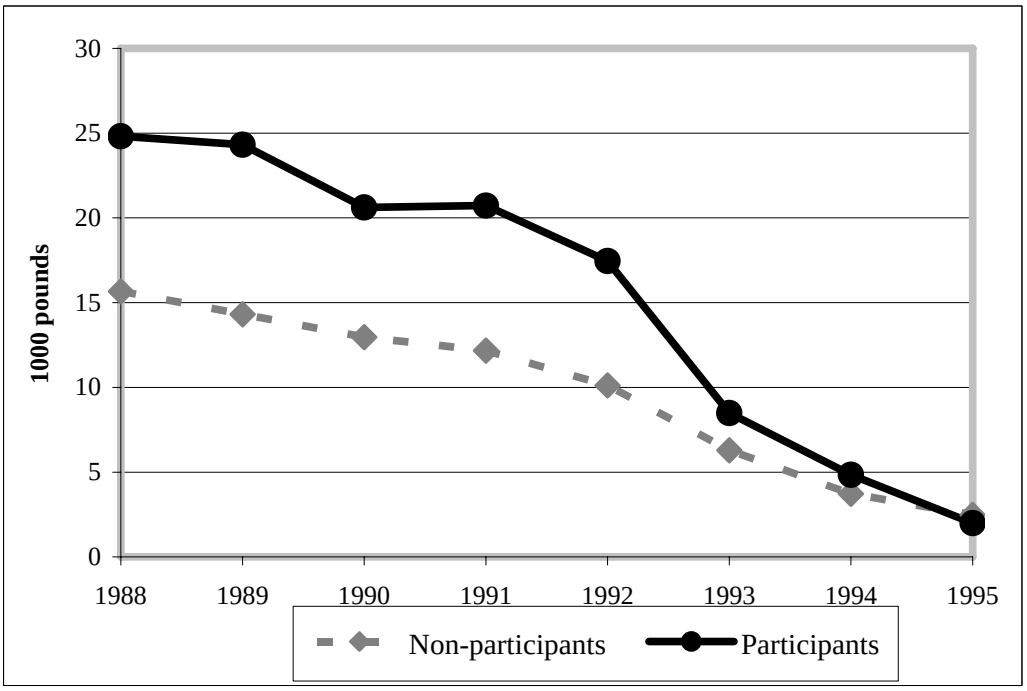
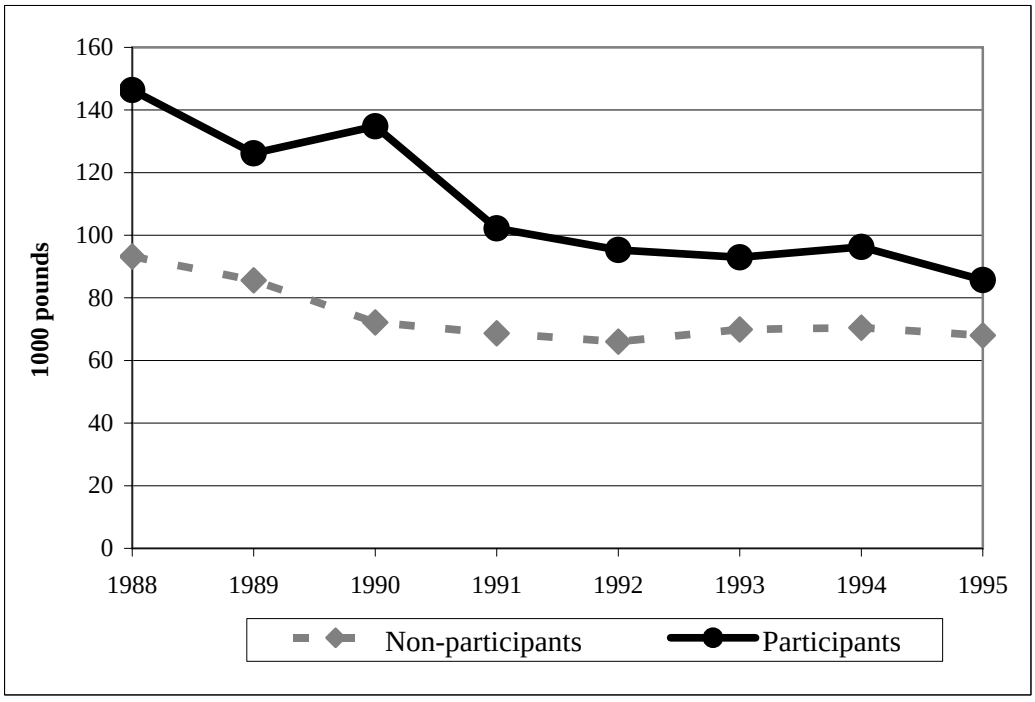


Figure 2.2 Average Releases for non-OD Chemicals, 1988-1995.



Chapter 3 Adoption of Pollution Prevention: The Role of Information Spillover, Mandatory Regulation, and Voluntary Program Participation

3.1 Introduction

Interest in promoting Pollution Prevention (P2) has been increasing since 1991. The passage of the Pollution Prevention Act (PPA) by the Congress in 1990 highlighted the recognition by policy makers that P2 has the potential to increase resource use efficiency, reduce pollution at source, prevent shifting of pollution from one medium to another, and reduce trace pollutants otherwise difficult to control (Khanna, 2006). As part of the PPA, facilities that are subject to the Toxics Releases Inventory (TRI) are required to disclose the number of incremental P2 activities for each listed chemicals from 1991 onward. Though the disclosure is required by the PPA, the adoption of P2 remains a voluntary initiative by firms.

Unlike end-of pipe technologies that are were likely to be available off the shelf, P2 technologies included modification of the production process and substitution of toxic materials with non-toxic or less toxic substances. These activities were more likely to be facility- and operation- specific and involved considerable information costs and uncertainty. Due to these operational challenges, the U.S. EPA established a P2 information clearinghouse to facilitate exchange of information (U.S.Environmental Protection Agency, 2009). Firms might learn about P2 technologies from neighbors through informal social interactions and sharing common resources (Besley and Case, 1993; Case, 1992; Griliches, 1957). Firms might also learn about P2 technologies from other firms in the same industry because they shared similar production technologies, supply chains, and trade publications (Dupuy, 1997; Harrington, 2008; Rothenberg and Zyglidopoulos, 2007). Thus learning from geographic or industrial neighbors could reduce

the information costs for other facilities and thus increasing the adoption of P2 in the next period. However, the performance of the P2 technology could be uncertain: negative shock by early adopters might have discouraged other facilities from adopting P2 in the next period. Since the objective of the PPA was set to encourage P2 through information exchange, an empirical examination is necessary to examine the effects of information spillovers on the adoption of P2.

In addition to information spillovers, the adoption of P2 technologies might have been motivated in part by regulatory pressures and in part by other voluntary commitments such as the adoption of an environmental management system. Firms that faced more inspections were more likely to adopt P2 technologies to improve compliance in the future (Sam, 2009). Firms participated in the 33/50 program were more likely to voluntarily adopt Total Quality Environmental Management (TQEM) system that emphasized source reduction as an integral component in the production processes (Sam et al., 2009). Firms might have discovered P2 opportunities or the cost-effectiveness of P2 while conducting those voluntary abatement efforts (Khanna et al. , 2009).

Program participants also might have chosen other abatement methods instead of P2 to achieve pollution reduction. Though the 33/50 program was established to promote the P2 ethic, none of the existing studies have empirically examined whether program participation had motivated the adoption of P2 technologies. Furthermore, the effect of program participation might not be limited to the participants. Theoretically, the experiences of the participants could demonstrate the effectiveness of P2 and lead to more P2 adoption by neighbors that had not participated in the program (Lyon and Maxwell, 2007). Empirically, such demonstration effect needs to be investigated because it depends on the effectiveness of the P2 technologies and the effect of information spillover.

The purpose of this chapter is twofold. First, we examine the extent to which the adoption of P2 technology was motivated by peers' prior P2 experience after controlling for pressures of mandatory regulations and voluntary program participation. Since facilities were more likely to learn from other facilities using the same types of chemicals, we separate the number of P2 technologies into P2 technologies adopted for 33/50 chemicals and the rest of the TRI chemicals. We examine the effect of neighbors' P2 experience on the adoption of P2 technologies for the respective chemicals. Second, we examine the extent to which program participation motivated P2 adoption for program participants and whether their experiences increased P2 adoption among neighbors.

To answer these questions, we conduct an empirical analysis on 6974 facilities that were eligible for the voluntary 33/50 program over the periods of 1991-1995. We estimate the number of P2 technologies adopted for 33/50 and rest of the TRI chemicals at the facility level with respect to the program participation, compliance costs to regulations, past P2 adoption by the neighbors, and the program participation ratio of the neighbors. We address the endogeneity of program participation with instrumental variables and control for location and industry fixed effects.

Our analysis shows that there was positive information spillover among facilities within the same industry. After controlling for information spillovers and regulatory pressures, program participants adopted more P2 technologies for 33/50 chemicals than non-participants. Program participation had little impact on the adoption of P2 technologies for the rest of the TRI chemicals. We also find that the 33/50 program played a limited role in disseminating P2 experiences from participants to other facilities, as we do not find a significant demonstration effect. Additionally, we find that facilities that emitted a greater amount of regulated toxic

releases adopted more P2 technologies, but the effects of other regulations varied by types of chemicals.

3.2 Related Literature

Existing literature has focused on the effects of environmental regulations on innovations in environmental technologies. Several empirical papers have been set forth to test the Porter hypothesis (Porter and van der Linde, 1995) that stringent environmental regulations could provide incentives for firms to innovate and develop more cost-effective methods of achieving regulatory compliance. Among those studies, a few of them have used patent applications and R&D expenditures to approximate environmental technology innovations and have used pollution abatement expenditures as proxies for compliance costs (Jaffe, et al., 2002). Other studies have tested the Porter hypothesis by examining the relationship between stringent environmental regulations and productivity (Berman and Bui, 2001; Gray and Shadbegian, 1998). Both types of empirical studies have yielded mixed conclusions. The conclusions are methodologically, time- and industry-specific. For example, studies on pulp and paper industry does not support the porter hypothesis (Press, 2007). Nevertheless, the general conclusions seem to be that environmental R&D and environmental patents applications were positively associated with the increase in pollution abatement expenditures and, in certain sectors, stringent regulations had increased the competitiveness of the firms.

Other empirical studies have directly examined the effects of environmental regulations on the adoption and diffusion of new environmental technology. Snyder et al. (2003) study the effect of environmental regulation on the adoption of a new processing technology in the chlorine manufacturing industry. They find that regulations directly imposed on chlorine production had no significant impact on technology adoption. Instead, end-users of chlorine

products were more likely to exit the market due to the regulations. Kerr and Newell (2003) study the effects of various environmental policies on the adoption of a new technology by U.S. refineries during the lead phasedown period of 1971 -1995. They find that the regulations on fuel additives and car fleets were the dominant factors in the adoption of the new technology. In addition, a few studies use interviews and surveys to examine firm's perceptions of environmental regulations and their decisions to adopt environmental technologies. For example, Dupuy (1997) find that firms undertake source reduction activities in anticipating greater enforcement stringency.

Besides mandatory regulations, several empirical studies have examined the effects of voluntary programs in promoting environmental technology innovation, diffusion, and adoption. Cleff and Rennings (1999) find that firms perceived such voluntary programs as eco-labels and voluntary commitments to be important in encouraging product and process innovation. Rennings et al. (2006) use data from German firms certified by the Eco-Audit and Management Scheme (EMAS) instituted in 1995 and find that the greater level of EMAS implementation had a positive effect on environmental process innovation. They also find that the EMAS had facilitated information spillovers as firms compared their environmental reports with others to generate ideas on their own environmental innovations. Wagner (2008) uses survey data from a broader scope of European firms and finds that the probabilities of both product and process innovations increased as the level of implementation of Environmental Management Systems (EMS) increased. A few studies have also shown that 33/50 program participation had led some firms to adopt Total Quality Environmental Management (TQEM). Sam et al. (2009) find that 33/50 program participants were more likely to adopt the TQEM system, a management system with emphasis on source reduction through product and process modifications. Khanna et al.

(2009) find that firms that adopted TQEM also adopted more P2 technologies, after controlling for level of pollution and endogenous TQEM adoption.

Furthermore, a few empirical papers have examined the role of community pressure in motivating the adoption of environmental technology and find mixed evidence. Blackman and Bannister (1998) find that community pressures from competing firms and local organizations were more effective than regulatory pressures in inducing the adoption of clean technology in the unregulated manufacturing sector in Mexico. However, Harrington (2008) only finds weak evidence to support that community pressures motivated the adoption of P2 technology.

Empirical and theoretical studies on technology adoption have noted that spillovers (social learning) occurring in networks leads to a greater adoption rate of new technology (Besley and Case, 1993; Doring and Schnellenbach, 2006; Griliches, 1957). A more recent study by Foster and Rosenzweig (1995) has used household level panel data in India and finds that farmers had higher profits and devoted more land to the high-yielding varieties if their neighbors were more experienced with the new technology. Munshi (2009) examines the adoption of high-yielding varieties among rice and wheat growers in India and also finds positive social learning effects. Additionally, he points out that the learning effect was weaker for rice growers than for wheat growers, because the yields of high-yielding rice varieties fluctuated more due to a greater degree of heterogeneity in growing conditions and practices among rice growers. Typically, these types of studies have assumed the structure of the social networks that farmers from the same village were considered as neighbors through whom they learned about the new technology.

In contrast to the above studies with observational data at the household level, the following studies have used individual level randomized experimental data. Instead of imposing the structure of the social networks, the following studies have surveyed individuals to identify

their social links. However, these studies have reached mixed conclusions on the effect of social learning on technology adoption. Kremer and Miguel (2007) have used a randomized experiment on the adoption of a deworming drug program in Africa and found that the participation rate of the deworming program was reduced when more friends (social contacts) were exposed to deworming. However, Oster and Thornton (2009) also have used a randomized experiment to examine peer effects on the adoption of a female hygiene technology in Nepal and found positive learning effect.

Both papers have outlined and investigated the following two mechanisms that could lead to positive peer effects: imitation and learning from peers about how to effectively use a new technology. However, both note that adoption by others can also provide information on the benefits of a new technology. This mechanism could lead to either positive or negative learning effects, depending on the effectiveness of the technology. Though the deworming technology is easy to adopt, Kremer and Miguel (2007) find that the benefit of deworming is less clear due to individual- and time-specific shocks to a person's health status. Oster and Thorton (2009) find that the female hygiene technology is difficult to use, but yields substantial benefit for all who have adopted it. In this case, learning about how to better use the technology leads to a greater adoption rate. Therefore, the conclusion on the effect of learning in the literature depends on the characteristics of the population and the effectiveness of the technology.

Our paper contributes to existing studies in the following ways. First, most empirical studies have focused on one specific technology to understand the effect of learning and technology adoption. We focus on a wide range of 33/50-eligible facilities and examine their adoptions of P2 technologies for 33/50 and for the rest of the TRI chemicals. To capture the effect of learning among neighbors, we include all TRI facilities within the same industry and

county and aggregate the number of P2 technologies adopted for 33/50 chemicals and the rest of TRI chemicals. We then examine the extent to which prior P2 experience of peers increased the adoption of P2 technologies by a facility on respective chemicals in the next period. Second, existing literature on voluntary environmental initiatives has examined the effect of program participation/certification on technology adoption; few have examined whether greater program participation by neighboring facilities led to a greater rate of P2 adoption. We include the percentages of program participants in the geographic and industrial networks to determine the indirect effect of program participation on other facilities. Third, previous studies on environmental regulation and technology adoption have focused on regulated pollutants. TRI chemicals are not directly regulated, but are indirectly regulated to the extent that they are precursors to regulated pollutants. We examine whether regulatory pressures were effective in motivating P2 adoption for those otherwise unregulated pollutants. We control for various regulatory pressures, such as designation of county attainment status, precursors to regulated pollutants, performance standards on Hazardous Air Pollutants (HAP), and plant specific inspections and enforcement activities. In our analysis, we compare those regulatory pressures with voluntary 33/50 program participation and information spillovers.

3.3 The Decision to Adopt P2 Technology

P2 includes such activities as spill and leak prevention, cleaning method modification, process modification, inventory control, and input substitution. These activities have the potential to increase the productivity of pollution-generating inputs or the efficiency of TRI chemicals. Given the level of output, a production process with P2 has the potential to reduce the use of the TRI chemicals, which would then lead to a reduction of input costs and a reduction in total toxic wastes and the treatment costs associated with end-of-pipe cleanup. Hence, compared

to other pollution control methods, P2 could lead to financial gain (King and Lenox, 2002). The adoption of new P2 technology, however, requires greater coordination within the facility among different production activities and may involve the costs of searching for appropriate technology, product and process modification, and employee training (Jaffe, et al., 2003). Initially, there could also be a considerable amount of uncertainty about the performance of the new technology (Kemp, 1998).

We assume a myopic facility makes the decision to adopt a P2 technology based on the expected net benefit of adoption. The process of adoption can be represented in two periods (Nakajima, 2007). In the first period, facilities with potentially higher net benefits from P2 adoption decide to adopt the P2 technology, even in the absence of regulatory pressures and voluntary program participation. In the following period, upon observing the information generated by adopters in the first period, facilities that have not adopted P2 would update their expectations of the P2 technology and make their decisions to adopt or not adopt. The information from early adopters may include procedural knowledge (know-how) and the performance of the P2 may be influenced by a stochastic shock.

Information on procedure know-how could increase the adoption of new technology, especially when the P2 technology is hard to use, but offers notable benefits (Oster and Thorton, 2009). The magnitudes of the learning effects depend on the characteristics of the population (Munshi, 2009). The effects of learning are expected to be stronger for homogenous populations than for heterogeneous populations. The information on the performance (effectiveness) of the P2 technology however could either lead to a greater rate of adoption (Oster and Thorton, 2009) or could deter future adoption (Kremer and Miguel, 2007). We expect to find a positive spillover

effect when the P2 technology is effective and a negative or insignificant effect when the P2 technology is ineffective.

We focus on two types of neighbors (networks): facilities in the same county and in the same industry. Facilities that are located in the same areas could gain access to the know-how on the P2 technology (Besley and Case, 1993; Case, 1992) either through informal social interactions, shared common resources, or a combination of both (Downing and White, 1986) . Facilities may also learn about the P2 technology from other facilities in the same industry since they are also more likely to share their experiences through trade publications (Dupuy, 1997) and to look for new ideas from each other's environmental reports (Rennings et al., 2006). Furthermore, related companies could be interested in exploring P2 opportunities if their common suppliers have started using P2 technology (Dupuy, 1997; Rothenberg and Zyglidopoulos, 2007).

The first hypothesis we test is that facilities adopted more P2 technologies if their neighbors had adopted more P2 technologies in the previous period. We expect that the late adopters could learn on how to better use the P2 technologies through early adopters (Oster and Thornton, 2009). However, we might find insignificant or even negative learning effect , when facilities were heterogeneous (Munshi, 2004) or and when the P2 was ineffective (Kremer and Miguel, 2007). Therefore, evidence of the information spillovers remains an empirical question to investigate.

The second hypothesis we test is that program participants adopted more P2 technologies than non-participants. Participants received public recognition for their proactive efforts, which reduced information asymmetry between the public and the firms. This could increase their incentives for other voluntary environmental efforts (Khanna and Anton, 2002). Program

participants might also have access to technical assistance from the government that could reduce the initial information barrier to adopting P2 technology (Howarth, et al., 2000; Lyon and Maxwell, 2007). Program participants might also have adopted more P2 since participation could led to internal change in the management philosophy and view toward environmental management, which encourage firms to reduce pollution at its source (Khanna, et al., 2009; Sam, et al., 2008). Firms might have recognized the advantages of eliminating some or more chemicals through P2 and thus reducing the need to report to TRI, thereby avoiding adverse publicity due to TRI releases. Additionally, program participants might have motivated other facilities to explore P2 opportunities through demonstration (Lyon and Maxwell, 2007), specifically through the geographic and industrial networks.

The last hypothesis we test is that facilities adopted more P2 if there were more program participants in their geographic and industrial networks. Since the net effects of learning depend on the characteristics of the population and the effectiveness of the P2 technology, the effect of demonstration might also depend on the performance of the P2 technology adopted by program participants and the similarities between program participants and their neighbors.

3.4 Empirical Method

To investigate the effects of information spillovers on adoption of P2, we set up a two-period model, as shown in equation [3-1]. The number of P2 technologies adopted by a facility in the current period depends on program participation P_i, the facility's anticipated compliance costs, adoption of P2 by neighbor facilities in the last period, location- and industry- specific effects, and public/community pressure. We aggregate the number of P2 technologies adopted by neighbor facilities in the last period assuming a facility updates its information on P2 adoption with respect to the total knowledge available in the networks. We use the lagged number of P2

technologies adopted by neighbors as explanatory variables to proxy for information effects, because the decisions to adopt P2 by the facility and its neighbors could be simultaneously determined.

Additionally, unobserved common factors at the neighborhood level could confound the information spillover effect (Manski, 1993). To distinguish the effects of information spill over from contextual effects, we control the network fixed effects by including dummy variables at the county and industry levels. Furthermore, program participation could be endogenous to the decision to adopt P2 due to unobserved facility characteristics. To account for endogenous program participation, we use instrumental variables. [28]

$$T_{it} = \beta_1 X_{it-1} + \beta_2 L_{-i,it-1} + \beta_3 G_i + \beta_4 P_{it} + u_{it} \qquad [3\text{-}1]$$

where T_{it} denotes the number of new P2 adopted by facility i over the period 1994-1995, X denotes a vector of facility specific explanatory variables , L'_{-i} denotes a vector of proxies for information spillover effects in the previous period, $G_i^{'}$ represents a vector of location and industry fixed effects, and P_{it} denotes program participation. $P_{is} = 1$ for year $t \geq s$ if the facility joined the program in year S , and $P_{is} = 0$ otherwise

3.4.1. Dependent Variables

We measure two sets of dependent variables: the number of P2 technologies adopted for 33/50 chemicals and the number of new P2 technologies adopted for the rest of the TRI chemicals. We refer them as *33/50 P2* and *Other P2* in our regressions. These two dependent variables are calculated for TRI facilities eligible for the 33/50 program. Since the reporting

[28] Around half of the facilities studied reported zero P2 adoption. A probit model would be more appropriate in this case. However, we encountered convergence problems when including neighborhood fixed effects. We therefore use a linear 2SLS model here, as suggested by Angrist (Angrist, 2001). Angrist shows that 2SLS yields similar results to those obtained using nonlinear estimation methods when estimating the average causal effect for limited dependent variables with endogenous variables.

threshold and requirement at the chemical level changes over time, we only focus on the chemicals that are part of the TRI throughout the study period. Out of 612 TRI chemicals, the reporting criteria remain constant for 295 chemicals in the study period. To calculate *Other P2,* we aggregate the total number of P2 technologies adopted for any of those 295 chemicals by facilities.

3.4.2. Information Spillover

Due to data availability, we focus on two types of neighbors (networks), facilities in the same county and facilities in the same industry. Facilities that have the same 3-digit SIC code are classified as belonging to the same industry. Although we focus on the 33/50–eligible facilities on the left-hand side, we include all TRI facilities to calculate the total number of 33/50 P2s and other P2s adopted by neighboring facilities in the same county and industry. In the end, we have four types of L'_{-i} variables to approximate the stock of available knowledge. We refer these four variables as: *Industry 33/50 P2*, *Industry Other P2*, *County 33/50 P2*, and *County Other P2*.

3.4.3. Number of Program Participants

To examine whether the presence of program participants in the neighborhood would affect a facility's P2 decision through demonstration, we include two variables: *County Participation Ratio* and *Industry Participation Ratio*. We calculate those ratios using the number of program participants in the same county and in the same industry divided by the total number of neighbors in the same county and in the same industry, respectively.

3.4.4. Instrumental Variables for Program Participation

They are *First Invitation Grou*p, *Firm's Prior Reduction of 33/50 Releases*, and *Facility's Share of TRI releases of Parent Company*. We have provided a detailed discussion on

these variables and shown that these are correlated with the participation decision in Chapter 2. To ensure the identification of equation [3-1], we argue that two of these variables are less likely to be correlated with a facility's P2 adoption, except through a facility's participation. We include the last variable in the determinants of P2 adoption for other TRI chemicals, and a detailed discussion is provided below.

The first excluded instrumental variable is *First Invitation Group.* It is not likely to directly affect P2 adoption at the facility level except through the facility's program participation, because parent companies typically have multiple facilities, and not all of which participated in the program. The second excluded instrumental variable is *Firm's Prior Reduction of 33/50 Releases.* It is also considered to be exogenous to P2 adoption from 1991 onward because the reduction of 33/50 releases preceded the mandatory reporting of P2 in the TRI, and this variable is defined at the parent company level. Since it focuses on 33/50 chemicals, it is likely to affect the P2 adoption for 33/50 chemicals, but only through the facility's participation in the program.

The last variable is the *Facility's Share of TRI releases of Parent Company.* We have shown in Chapter 2 that the relatively larger TRI emitters within a parent company were more likely to participate in the program. Since this variable is defined with pre-program characteristics and includes all TRI chemicals, it is unlikely to be correlated with P2 adoption of 33/50 chemicals in 1991-1995, except through program participation. However, since this variable includes all other TRI chemicals, it could be correlated with P2 adoption of other TRI chemicals. We conduct an orthogonal test on this variable using the procedure described in Baum et al. (2003). We find this variable directly affect the decision to adopt P2 for other TRI chemicals but does not directly affect the decision to adopt P2 for 33/50 chemicals. We therefore

include this variable as an explanatory variable when estimating the determinants of P2 adoption for other TRI chemicals.

3.4.5. Other Explanatory Variables

We include the following variables to approximate the existing and anticipated regulatory pressures at the facility level, and these explanatory variables influence both P2 and program participation decisions. We use the sum of releases of chemicals included in various environmental regulations to approximate the existing costs of compliance. These chemicals include precursors of the criteria for air pollutants (Greenstone, 2003), toxic chemicals specified by the Resource Conservation and Recovery Act (RCRA), chemicals known as Extremely Hazardous Substances listed in the Emergency Planning and Community Right-to-Know Act (EPCRA), chemicals included in the Comprehensive Environmental Response Act (CERLA, commonly known as Superfund), and chemicals included in the Federal Insecticide, Fungicide, and Rodenticide Act (FIFRA). We refer this variable as *Regulated Releases* in our regressions and it is in logarithmic form. We expect to see a positive association between regulated releases and P2 adoption, provided there is a certain level of synergy between regulated pollutants and unregulated TRI chemicals. We include one variable, *Total Inspections,* to represent regulatory enforcement activities. This variable includes the total number of inspections levied on a facility under the CAA, Clean Water Act (CWA), and RCRA. To proxy the anticipated compliance costs, we use the ratio of HAP releases to total TRI releases at the facility level, denoted as the *HAP-TRI ratio*. To avoid simultaneity, these variables defined at the facility level are lagged by one year in equation [3-1].

In addition, we control for the number of chemicals reported at the inception of the TRI, since the number of P2 technologies adopted is positively associated with the number of

chemicals used by the facilities. We refer this variable as *Number of Core Chemicals*, and it is defined as the total number of TRI chemicals reported in 1988.

We have the following variables to control for county- and state level-regulatory stringency. These variables are shown to be correlated with the change of toxic releases and program participation in Chapter 2. These variables are: *County Nonattainment Status*, *County Median Income* (household income), and *State LCV Score.*

3.5 Data Description

The TRI dataset provides chemical-specific P2 adoptions and releases, names of the parent companies, industry classifications, and the locations of the TRI facilities. We compile a panel dataset for all TRI facilities for the period of 1991-1995, from which we identity the 33/50-eligible facilities. Since we focus on information spillover within counties and industries, we exclude the counties and industries that only had a few TRI facilities.[29] Because of this restriction we have a balanced panel data set with 6974 facilities classified in 107 industries and 752 counties. We identify 605 facilities as program participants.[30]

We obtain the list of TRI chemicals that are precursors of the criteria air pollutants from Greenstone (2003) . The list of TRI chemicals targeted by various environmental regulations and the information on chemical deletions and modifications come from the EPA (U.S. Enviornmental Protection Agency, 2010 a,b) .

Facility-specific data on the numbers of violations, penalties, and inspections for compliance with the CAA, CWA, and RCRA are obtained from the EPA's Integrated Data for Enforcement Analysis System (U.S. Environmental Protection Agency, 2007a). These data are merged with the TRI data using the unique TRI identifier for each facility. The reported location

[29] We drop the counties that had fewer than 5 TRI facilities and industries that had fewer than 10 TRI facilities in any given year from 1991 to 1995.
[30] In Chapter 2 and Chapter 3, we have included 1335 participating facilities without the restriction.

of a facility in the TRI dataset is used to merge the above data with each county's median income from the 1990 census as well as with the county's attainment status (U.S. Environmental Protection Agency, 2007b) and with state-level scores on environmental legislation (League of Conservation Voters, 2007). We present the summary statistics on the variables used in the regressions in Table 3.1.

3.6 Results

3.6.1. Program Participation and P2 adoption

First, we estimate the effects of program participation and regulatory pressures on P2 adoption over the period of 1992-1995. Table 3.2 presents the results on 33/50 P2 and Table 3.3 presents the results on other P2.

We find that, in the absence of information spillover, program participants adopted more 33/50 P2s (Table 3.2, Row 1). Across all models in Table 4.2, program participants adopted 1.007 to 1.217 more P2 technologies for 33/50 chemicals, as compared to the non-participants. We also find that facilities emitting a larger amount of regulated releases adopted more P2 for 33/50 chemicals (Table 3.2, Row 3). Contrary to previous studies (Khanna, et al., 2009; Harrington, et al., 2008) , we do not find that a greater rate of inspections caused the facilities to adopt more P2s (Table 3.2 and Table 3.3, Row 4). Since chemicals are part of the 189 chemicals that are listed as Hazardous Air Pollutants (HAP), the future regulation on HAP pollutants created incentives for facilities to adopt P2 technologies. We find that facilities had greater HAP-TRI ratio adopted more 33/50 P2 technologies (Table 3.2, Row 4). Previous studies raise the concern that the facilities in a nonattainment county were more likely to use end-of-pipe abatement methods, such as scrubbers, to control air pollutants (Greenstone, 2003). We find weak evidence that the designation of county attainment status on criteria air pollutants

encouraged P2 adoption. The effects of county non-attainment status were positive and statistically significant before we include county fixed effects and industry fixed effects (Table 3.2 and Table 3.3, Row 5). This could be due to the fact that few counties had attainment statuses varied over time. Facilities that reported a greater number of chemicals in 1988 adopted more P2s for 33/50 chemicals. In addition, there was a negative trend in the number of P2 technologies adopted for 33/50 chemicals, as the time dummies were statistically significant and negative. Since the TRI facilities only report the incremental P2 activities on an annual basis, the marginal cost of abatement was likely to increase with additional P2 technologies adopted. We have observed the decline of 33/50 releases, particularly in the beginning of the program (Chapter 2). It is likely that facilities exhausted their P2 opportunities at the beginning of the program. Therefore, we observe a negative trend in the number of 33/50 P2s.

Similar to the findings in Table 3.2, we find that facilities emitting a greater amount of regulated releases and reporting a greater number of chemicals in 1988 adopted more other P2s (Table 3.3). Though the 33/50 program did not target other TRI chemicals, it is speculated that program participation might have spurred changes in environmental management philosophy, which could encourage the adoption of P2 technologies in general. However, the effect of program participation was limited to 33/50 chemicals. Program participation had no impact on the number of other P2s adopted (Table 3.3, Row 1). Facility that accounted for larger share of TRI releases by the parent company adopted fewer P2s for other TRI chemicals (Table 3.3, Row 2). Future regulation on the HAP chemicals did not encourage the adoption of P2 for other TRI chemicals. On the contrary, it had a negative effect on other P2 adopted (Table 3.3, Row 4). Furthermore, the State LCV scores did not have any impact on the adoption of 33/50 P2 but we find weak evidence that it discouraged the adoption of other P2 (Table 3.3, Row 7). While we

find a negative trend in the adoption of 33/50 P2s, we do not observe a significant time trend in the adoption of other P2s.

3.6.2. Information Spillovers and P2 adoption

Second, we examine the effects of information spillovers on P2 adoption for 33/50 chemicals and other TRI chemicals in Table 3.4 and Table 3.5, respectively. Consistent with our findings in Table 3.2, the effect of program participation on 33/50 P2 was statistically significant across all models in Table 4.4 (Table 3.4, Row 1).

The effects of 33/50 P2s adopted by neighbors on the adoption of 33/50 P2 by a facility are examined in the following ways. Models XI to XIV examine the information spillovers in the same industry. We start with a parsimonious specification in Model XI with the effect of program participation and the number of 33/50 P2s adopted by industry neighbors. We add the participation ratio in the industry in Model XII. We include the industry fixed effects and exclude the industry program participation ratio in Model XIII, and include both participation ratio and industry fixed effects in Model XIV.

We find that the total number of 33/50 P2s adopted by other facilities in the same industry increased the number of 33/50 P2 adopted by a facility (Table 3.4, Row 5). One additional increase in the number of P2 adopted by neighbors led to a 0.001 increase in the number of 33/50 P2 adopted by a facility. This effect was small compared to the direct impacts of program participation and regulatory pressures. A typical industry in our sample had on the average 415 facilities. Even if half the facilities had adopted 33/50 P2 technologies in the last period, the likelihood of 33/50 P2 adoption by a facility in that industry would only increase by 20%. We do not find that a higher ratio of program participants in the industry increased the number of 33/50 P2s adopted by a facility (Table 3.4, Row 6).

Models XV to XVIII examine the information spillovers in the same county. Model XV examines the effect of program participation and the number of 33/50 P2s adopted by neighbors in the same county. We add the participation ratio in the county in Model XVI. We include the county fixed effects and exclude the county participation ratio in Model XVII, and include both the participation ratio and county fixed effects in Model XVIII.

We find that 33/50 P2s adopted by other facilities in the same county did not significantly increase the number of 33/50 P2 adopted by a facility, after the county fixed effects are included (Table 3.4, Row 7). Moreover, we do not find that a higher ratio of program participants in the county increased the adoption of 33/50 P2 after controlling for information spillovers among the neighbors (Table 3.4, Row 9).

Table 3.5 presents the results on the effects of information spillovers for other P2. The models in Table 3.5 follow the same order as the ones in Table 3.4. Across all the models, we do not find that 33/50 program participation caused participants to adopt more P2 technologies for other TRI chemicals. We find that other P2s adopted by facilities in the same industry increased the number of other P2s adopted by a facility. The magnitudes of the information spillovers are similar to the ones reported in Table 3.4. Additionally, we find that the effect of information spillover in the county was not significant after controlling for county fixed effects. The program participation ratios in the county and industry did not significantly affect the adoption of other P2.

In sum, our results indicate that facilities were more likely to learn from their industry peers on how to adopt P2 technologies. The direct impact of program participation was only evident for chemicals targeted by the program. The pressures from regulations influenced the adoption of 33/50 P2 and other P2 differently. Greater ratios of program participation in the networks did not significantly motivate P2 adoption.

3.7 Conclusions

In this chapter, we use the data from 6974 facilities that were eligible for the voluntary 33/50 program to examine the extent to which program participation and information spillover motivated P2 adoption for both 33/50 chemicals and other TRI chemicals. We use the one-year lagged total number of P2 adopted by other TRI facilities in the same county and industry to approximate the available knowledge on P2. After controlling for endogenous program participation and the fixed effects at the county and industry levels, we find that the effects of information spillovers differed by types of chemicals and types of neighborhoods.

Though the voluntary program was not intended to address pollution problems associated with other TRI chemicals, a few researchers have argued that voluntary programs can be used to promote environmental technology change by providing informational subsidies in terms of technical assistance on the adoption of best practice (Lyon and Maxwell, 2007).

Our findings indicate that if policy makers were to rely solely on the information spillover to generate technology change, there could be several limitations on the effectiveness of information subsidies. First of all, the magnitude of the effects could be relatively small in comparison to the direct impacts of regulatory pressures. The information generated by early adopters could be relevant only to facilities in the same industry that have similar production technologies and outputs. Future policies to encourage the adoption of new environmental technology should thus focus on firms that are closely related to one another.

Second, the direct impact of the voluntary program on P2 was limited to the targeted chemicals only. Facilities were not motivated to adopt more P2 in the presence of participants in their geographic and industrial networks. These results could be explained by the fact that the P2 technologies reported by TRI facilities were chemical-specific and did not include other

information on changes in environmental management systems. Nevertheless, they suggest that voluntary programs targeted at certain toxic chemicals may not induce environmental technology change to address a wide spectrum of toxic pollution problems.

Last, it is essential to keep in mind that the effects of information spillovers may vary by the type of networks through which firms interact with each other. Previous studies find that the effect of learning was weaker for a heterogeneous population (Munshi, 2004). We find that facilities in the same industry were more likely to learn from each other, but facilities from the same county were less likely to do so. This result suggests that there are greater similarities between industry neighbors than between geographic neighbors. In that sense, facilities may have stronger incentives to imitate their industry peers or to learn how to better use a technology from their industry peers. Due to data availability, we have assumed that facilities in the same industry and in the same county are more likely to learn from each other, and we have treated the neighbors from the same county and the same industry as equally important. Our results suggest two possible extensions that future studies could explore. First, information from industry peers should probably be given greater weight than information from the geographic neighbors when examining adoption and diffusion of environmental technology. Second, we do not have information on the supply chains through which facilities are connected. Within the same industry, facilities may have learned more from the peers with whom they share common suppliers or end-users. Thus, those peers should be given greater weight than the rest of the facilities in the industry. Future study on information spillovers could address this limitation by constructing industry networks with information on supply chains.

3.8 Tables

Table 3.1 Summary Statistics, 1991-1995.

Variables	Mean	Std.	Min	Max
First invitation group	0.371	0.483	0.0	1.0
Program participation	0.126	0.332	0.0	1.0
Facility's share of TRI releases of parent company	0.411	0.424	0.0	1.0
Prior reduction of 33/50 releases(thousand pounds)	0.495	2.053	-57.0	16.9
Number of core chemicals in 1988	4.296	5.069	0.0	80.0
Regulated releases in 1988(Log)	11.895	2.918	0.0	19.5
All inspections	1.160	1.774	0.0	22.0
HAP-TRI	0.795	0.275	0.0	1.0
Number of 33/50 P2s adopted	3.596	6.151	0.0	84.0
Number of Other P2s adopted	2.968	8.082	0.0	112.0
Industry Participation Ratio	4.480	2.835	0.0	18.2
Industry 33/50 P2s	971.708	965.754	5.0	4337.0
Industry Other P2s	945.404	1006.370	0.0	3779.0
County 33/50 P2s	171.257	307.301	0.0	1686.0
County Other P2s	165.287	284.313	0.0	1481.0
County Participation Ratio	3.763	4.508	0.0	60.0
County non-attainment status	0.978	0.887	0.0	3.0
County median income(thousand dollars)	30.956	6.724	15.9	56.3
State LCV score	37.681	23.778	0.0	196.0

Table 3.2 Determinants of P2 Adoption: Program Participation Effects on Adoption of 33/50 P2 Adopted, 1992-1995.

Variables	I 33/50 P2	II 33/50 P2	III 33/50 P2	IV 33/50 P2	V 33/50 P2
Program Participation	1.165**	1.217**	1.210**	1.200**	1.007*
	[0.563]	[0.584]	[0.617]	[0.556]	[0.594]
Regulated releases in 1988	0.060***	0.060***	0.061***	0.055***	0.060***
	[0.007]	[0.007]	[0.006]	[0.007]	[0.006]
All inspections	-0.031**	-0.031**	-0.031**	-0.024*	0
	[0.014]	[0.014]	[0.014]	[0.014]	[0.014]
HAP-TRI	0.407***	0.405***	0.406***	0.353***	0.096*
	[0.064]	[0.064]	[0.064]	[0.065]	[0.057]
County Nonattainment Status	0.048**	0.048**	0.048**	0.054	0.028
	[0.024]	[0.024]	[0.024]	[0.053]	[0.024]
LCV score	0	0	0	0	0
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Number of core chemicals in 1988	0.073***	0.074***	0.074***	0.083***	0.062***
	[0.010]	[0.010]	[0.010]	[0.010]	[0.011]
County median income	0.005	0.005	0.005	0.022	0.001
	[0.004]	[0.004]	[0.004]	[0.051]	[0.004]
County Participation Ratio		-0.007		0.008	
		[0.007]		[0.007]	
Industry participation ratio			-0.005		-0.008
			[0.013]		[0.014]
Year 1992	-0.384***	-0.377***	-0.382***	0.180***	-0.856***
	[0.119]	[0.120]	[0.120]	[0.029]	[0.247]
Year 1993	-0.402***	-0.386***	-0.393***	0.152***	-0.867***
	[0.119]	[0.122]	[0.123]	[0.024]	[0.248]
Year 1994	-0.455***	-0.439***	-0.446***	0.097***	-0.918***
	[0.118]	[0.120]	[0.122]	[0.019]	[0.248]
Year 1995	-0.551***	-0.535***	-0.541***	-0.581***	-1.012***
	[0.118]	[0.120]	[0.122]	[0.117]	[0.248]
County fixed effects				Included	
Industry fixed effects					Included
Observations	27,896	27,896	27,896	27,896	27,896
Number of facilities	6974	6974	6974	6974	6974
R-squared	0.23	0.229	0.229	0.297	0.279
P-Value of over identification test	0.275	0.291	0.28	0.37	0.205
Weak identification test	40***	37.86***	35.72***	43.34***	36.01***

Note: Models are estimated on a balanced panel using pooled 2SLS. Instrumental variables for the participation variable include first invitation group, firm's prior reduction of 33/50 releases and facility's share of TRI releases in the parent company. Robust standard errors clustered at the facility level in brackets. *** p<0.01, ** p<0.05, * p<0.1

Table 3.3 Determinants of P2 Adoption: Program Participation Effects on Adoption of Other P2, 1992-1995.

Variables	VI Other P2	VII Other P2	VIII Other P2	IX Other P2	X Other P2
Program Participation	0.028	0.141	0.26	0.189	1.278
	[0.855]	[0.958]	[1.203]	[0.811]	[1.107]
Facility's share of TRI releases of parent company	-0.208***	-0.220***	-0.232**	-0.199***	-0.296***
	[0.067]	[0.075]	[0.091]	[0.072]	[0.087]
Regulated releases in 1988	0.032***	0.032***	0.033***	0.029***	0.047***
	[0.008]	[0.008]	[0.008]	[0.009]	[0.008]
All inspections	-0.018	-0.019	-0.017	-0.014	-0.011
	[0.019]	[0.019]	[0.019]	[0.018]	[0.018]
HAP-TRI	-0.293***	-0.295***	-0.295***	-0.259***	-0.472***
	[0.083]	[0.083]	[0.083]	[0.081]	[0.079]
County Nonattainment Status	0.046*	0.047*	0.047*	0.074	0.02
	[0.027]	[0.027]	[0.027]	[0.050]	[0.028]
LCV score	-0.001**	-0.001**	-0.001**	0	-0.001
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Number of core chemicals in 1988	0.186***	0.186***	0.187***	0.185***	0.152***
	[0.018]	[0.018]	[0.018]	[0.018]	[0.019]
County median income	0.004	0.004	0.004	0.099	0
	[0.004]	[0.004]	[0.004]	[0.096]	[0.004]
County Participation Ratio		-0.008		-0.007	
		[0.010]		[0.009]	
Industry participation ratio			-0.014		-0.023
			[0.021]		[0.021]
Year 1992	0.128	0.141	0.142	0.113***	-0.206
	[0.135]	[0.139]	[0.143]	[0.036]	[0.328]
Year 1993	0.13	0.153	0.162	0.109***	-0.188
	[0.134]	[0.143]	[0.154]	[0.029]	[0.328]
Year 1994	0.09	0.112	0.122	0.073***	-0.233
	[0.133]	[0.141]	[0.151]	[0.021]	[0.328]
Year 1995	0.001	0.023	0.033	-0.149	-0.314
	[0.132]	[0.140]	[0.149]	[0.186]	[0.329]
County fixed effects				Included	
Industry fixed effects					Included
Observations	27,896	27,896	27,896	27,896	27,896
Number of facilities	6974	6974	6974	6974	6974
R-squared	0.191	0.191	0.19	0.252	0.207
P-Value of over identification test	0.823	0.798	0.741	0.924	0.714
Weak identification test	47.08	37.67	21.04	56.07	25.39

Models are estimated on a balanced panel using pooled 2SLS. Instrumental variables for the participation variable include first invitation group, and firm's prior reduction of 33/50 releases. Robust standard errors clustered at the facility level in brackets, *** p<0.01, ** p<0.05, * p<0.1

Table 3.4 The Effects of Information Spillovers and Program Participation on the Adoption of 33/50 P2, 1992-1995.

	Industry Peer Effects				County Peer Effects			
Variables	**XI**	**XII**	**XIII**	**XIV**	**XV**	**XVI**	**XVII**	**XVIII**
Program Participation	1.388**	1.376**	1.070*	0.978*	1.072*	1.101*	1.257**	1.201**
	[0.560]	[0.606]	[0.560]	[0.593]	[0.562]	[0.582]	[0.573]	[0.556]
Regulated releases in 1988	0.065***	0.068***	0.059***	0.060***	0.060***	0.060***	0.055***	0.055***
	[0.007]	[0.006]	[0.007]	[0.006]	[0.007]	[0.007]	[0.007]	[0.007]
All inspections	-0.015	-0.011	0	0	-0.027*	-0.027*	-0.025*	-0.024*
	[0.014]	[0.014]	[0.014]	[0.014]	[0.014]	[0.014]	[0.014]	[0.014]
HAP-TRI	0.247***	0.237***	0.099*	0.097*	0.409***	0.407***	0.352***	0.353***
	[0.062]	[0.062]	[0.057]	[0.057]	[0.064]	[0.064]	[0.065]	[0.065]
Industry 33/50 P2	0.001***	0.001***	0.001**	0.001**				
	[0.000]	[0.000]	[0.000]	[0.000]				
Industry participation ratio		-0.024		-0.009				
		[0.015]		[0.017]				
Industry fixed effects			Included	Included				
County 33/50 P2					0.001***	0.001***	0.0008	0.0003
					[0.000]	[0.000]	[0.001]	[0.001]
County participation ratio						-0.006		0.008
						[0.007]		[0.007]
County fixed effects							Included	Included
County Nonattainment Status	0.027	0.027	0.033	0.033	0.007	0.007	0.057	0.053
	[0.021]	[0.021]	[0.021]	[0.021]	[0.025]	[0.025]	[0.052]	[0.053]
Number of core chemicals in 1988	0.057***	0.059***	0.061***	0.062***	0.073***	0.074***	0.083***	0.083***
	[0.010]	[0.010]	[0.011]	[0.011]	[0.010]	[0.010]	[0.010]	[0.010]
Year 1992	-0.510***	-0.514***	-0.028	-0.022	-0.254***	-0.251***	0.788	0.799
	[0.069]	[0.069]	[0.191]	[0.191]	[0.065]	[0.065]	[1.410]	[1.410]

Table 3.4 (Cont.)

	Industry Peer Effects				County Peer Effects			
Variables	**XI**	**XII**	**XIII**	**XIV**	**XV**	**XVI**	**XVII**	**XVIII**
Year 1993	-0.497***	-0.472***	-0.023	-0.006	-0.265***	-0.254***	0.768	0.768
	[0.066]	[0.068]	[0.188]	[0.189]	[0.063]	[0.064]	[1.410]	[1.410]
Year 1994	-0.541***	-0.512***	-0.069	-0.051	-0.316***	-0.306***	0.715	0.714
	[0.066]	[0.067]	[0.188]	[0.189]	[0.063]	[0.064]	[1.409]	[1.409]
Year 1995	-0.613***	-0.582***	-0.149	-0.131	-0.407***	-0.396***	0.621	0.62
	[0.066]	[0.066]	[0.186]	[0.187]	[0.063]	[0.063]	[1.409]	[1.409]
Observations	27,896	27,896	27,896	27,896	27,896	27,896	27896	27,896
R-squared	0.249	0.25	0.278	0.279	0.233	0.233	0.296	0.297
P-Value of over identification test	0.412	0.263	0.29	0.23	0.323	0.326	0.403	0.37
Weak identification test	40.01***	36.3***	40.26***	36.24***	40.08***	38***	40***	43.34***

Models are estimated on a balanced panel using pooled 2SLS. Instrumental variables for the participation variable include Instrumental variables for the participation variable include first invitation group, firm's prior reduction of 33/50 releases, and facility share of TRI releases in the parent company. Robust standard errors clustered at the facility level in brackets, *** p<0.01, ** p<0.05, * p<0.1

Table 3.5 The Effects of Information Spillovers and Program Participation on the Adoption of Other P2, 1992-1995.

	Industry Peer Effects				County Peer Effects			
Variables	**XIX**	**XX**	**XXI**	**XXII**	**XXIII**	**XIV**	**XXV**	**XVI**
Program Participation	0.668	1.359	1.226	1.013	0.013	0.053	0.099	0.099
	[0.854]	[1.220]	[1.109]	[0.873]	[0.854]	[0.955]	[0.875]	[0.875]
Facility's share of TRI releases of parent company	-0.220***	-0.289***	-0.292***	-0.267***	-0.224***	-0.224***	-0.188**	-0.188**
	[0.066]	[0.092]	[0.087]	[0.071]	[0.068]	[0.076]	[0.076]	[0.076]
Regulated releases in 1988	0.039***	0.041***	0.047***	0.046***	0.033***	0.033***	0.029***	0.029***
	[0.008]	[0.007]	[0.008]	[0.008]	[0.008]	[0.008]	[0.009]	[0.009]
All inspections	-0.012	-0.009	-0.011	-0.011	-0.013	-0.012	-0.013	-0.013
	[0.019]	[0.019]	[0.018]	[0.018]	[0.019]	[0.019]	[0.018]	[0.018]
HAP-TRI	-0.405***	-0.414***	-0.473***	-0.472***	-0.293***	-0.282***	-0.259***	-0.259***
	[0.082]	[0.082]	[0.079]	[0.079]	[0.083]	[0.082]	[0.081]	[0.081]
Industry other P2	0.001***	0.001***	0.001***	0.001***				
	[0.000]	[0.000]	[0.000]	[0.000]				
Industry participation ratio		-0.046*	-0.022					
		[0.026]	[0.026]					
Industry fixed effects			Included					
County other P2					0.001***	0.005***	0.001	0.001
					[0.000]	[0.001]	[0.001]	[0.001]
County participation ratio						-0.007	-0.006	
						[0.010]	[0.010]	
County fixed effects							Included	Included
County non-attainment status	0.005	0.003	0.011	0.013	-0.02	-0.007	0.068	0.068
	[0.024]	[0.025]	[0.026]	[0.025]	[0.030]	[0.030]	[0.050]	[0.050]

Table 3.5 (Cont.)

	Industry Peer Effects				County Peer Effects			
Variables	**XIX**	**XX**	**XXI**	**XXII**	**XXIII**	**XIV**	**XXV**	**XVI**
Number of core chemicals in 1988	0.152***	0.156***	0.152***	0.151***	0.185***	0.182***	0.185***	0.185***
	[0.018]	[0.017]	[0.019]	[0.019]	[0.018]	[0.018]	[0.018]	[0.018]
Year 1992	-0.148**	-0.134*	-0.117	-0.119	0.111	0.111	2.84	2.84
	[0.070]	[0.072]	[0.124]	[0.122]	[0.070]	[0.072]	[2.655]	[2.655]
Year 1993	-0.142**	-0.076	-0.089	-0.115	0.099	0.099	2.826	2.826
	[0.065]	[0.079]	[0.124]	[0.119]	[0.066]	[0.072]	[2.655]	[2.655]
Year 1994	-0.188***	-0.122	-0.135	-0.163	0.064	0.061	2.792	2.792
	[0.065]	[0.076]	[0.124]	[0.121]	[0.066]	[0.071]	[2.653]	[2.653]
Year 1995	-0.249***	-0.179**	-0.194	-0.223*	-0.006	-0.023	2.727	2.727
	[0.066]	[0.077]	[0.123]	[0.120]	[0.065]	[0.069]	[2.652]	[2.652]
Observations	27,896	27,896	27,896	27,896	27,896	27,896	27,896	27,896
R-squared	0.207	0.195	0.208	0.212	0.192	0.193	0.252	0.252
Number of facilities	6974	6974	6974	6974	6974	6974	6974	6974
P-Value of over identification test	0.965	0.785	0.716	0.844	0.821	0.823	0.953	0.953
Weak identification test	47.83***	21.14***	24.98***	48.11***	46.91***	37.53***	47.99***	47.99***

Note: Models are estimated on a balanced panel using pooled 2SLS. Instrumental variables for the participation variable include first invitation group and firm's prior reduction of 33/50 releases. Robust standard errors clustered at the facility level in brackets, *** p<0.01, ** p<0.05, * p<0.1

Chapter 4 Pollution Prevention by the Voluntary 33/50 Program: Implications for Toxic Releases and Recycling

4.1 Introduction

Over the last decade, policy makers have emphasized their preference for P2[31] over end-of-pipe control methods. This follows the recognition that P2 has the potential to eliminate and reduce the quantity of hazardous pollutants at source before the point of generation through changes in input use and manufacturing processes. When compared to P2 techniques, recycling procedures are most likely to take place after the pollutants have been generated. Moreover, recycling procedures are mostly designed to recover valuable materials that can be reused in manufacturing processes rather than to eliminate the wastes from the source. Therefore, using recycling methods may result in shifting pollutants across environmental media. Additionally, storage, transportation and recovery of recycled chemicals could still pose potential environmental risks, since recycling processes may generate their own pollution and waste materials that cannot be recovered from recycling have to be treated or disposed elsewhere.

Given these advantage of P2 over other pollution control methods, the National Pollution Prevention Act of 1990 (PPA) established P2 as the preferred approach in the pollution control hierarchy, and declared that "pollution should be prevented or reduced at the source whenever feasible, pollution that cannot be prevented should be recycled in an environmentally safe manner whenever feasible; pollution that cannot be prevented or recycled should be treated in an environmentally safe manner, and disposal or other release into the environment should only be employed as the last resort and should be conducted in an environmentally safe manner"(U.S.

[31] EPA defines P2 as "reducing or eliminating waste at the source by modifying production processes, promoting the use of non-toxic or less-toxic substances, implementing conservation techniques, and re-using materials rather than putting them into the waste stream." It is used interchangeably with source reduction (U.S. Environmental Protection Agency, 2006).

Environmental Protection Agency, 1990). To promote public support and record the progress on P2, the PPA also amended the TRI by requiring additional reporting on waste management and P2 activities.

To encourage a more holistic approach to pollution control and create an ethic of P2, several voluntary environmental programs have been initiated (Khanna, 2006). This chapter focuses on the first, the 33/50 voluntary program, which encouraged P2 as the preferred approach to abate 33/50 releases. To encourage a reduction in releases to all media, the program did not set chemical- or media-specific targets. Firms were given the flexibility to select abatement methods and set their own reduction targets, but were encouraged to modify production processes, substitute input chemicals, and adopt P2 technologies to reduce their emissions from source.

Anecdotal evidence suggests that participating firms were motivated to choose P2 as their top priority and seek methods to reduce pollution from source, in order to meet their commitment to the 33/50 program (Zats and Harbour, 1999). One research also shows that 33/50 participation led some firms to adopt Total Quality Environmental Management (TQEM) that incorporates environmental quality attributes into product and process development, and emphasizes a philosophy of reduction of wastes at source (Khanna, et al., 2009; Sam, et al., 2009). Such firms might have been more likely to resort to P2 to reduce 33/50 releases as they recognized the cost-savings and efficiency gains associated with P2.

However, the 33/50 program might have led to other abatement methods that were lower in the pollution control hierarchy. 33/50 program only targeted reductions in aggregate on-site and off-site releases and did not specify any goals for reduction in total waste. Since P2 was a relatively new concept to firms in the early 1990s, adopters could face costs of learning,

searching, and uncertainties. As a result, program participants might have used abatement methods that were more likely to be readily available instead of P2 to reduce 33/50 releases. One study finds that 33/50 program participants significantly increased their transfers for off-site recycling than non-participants in all industrial sectors, except for facilities in the chemical sector (Gamper-Rabindran, 2006). In that sense, the 33/50 program might resulted in an increase in total 33/50 emissions.

The purpose of this chapter is threefold. First, we seek to examine the extent to which any reductions in 33/50 releases were achieved using P2 methods. Despite the recognition of P2 as the preferred approach to reduce pollution by policy makers, few empirical papers have examined the effectiveness of P2 in reducing toxic wastes (except for Harrington et al. (2008)). Facilities might adopt P2 simply to provide an outward signal of their efforts to be environmentally friendly, but might not have made any fundamental changes in their operations. Even if P2 was adopted and implemented successfully, P2 might have improved production efficiency and reduced pollution intensity. This might enable firms to produce more outputs which led to an increase in 33/50 releases.

Given that the effect of P2 adoption on toxic emissions might depend on total production, we examine the effects of P2 technologies separately for the Ozone Depleting (OD) chemicals and the rest of the 33/50 chemicals, since the OD chemicals were required by the Montreal Protocol to be phased out by 1996. Facilities might have to adopt P2 to modify their production processes and to substitute inputs in order to eliminate OD chemicals. In addition, we also consider the impact of P2 on the release of 33/50 chemicals based on toxicity of the chemicals. Facilities might have favored adoption of P2 to reduce or eliminate the use of highly toxic chemicals, thus avoid pubic and regulatory scrutiny created by being reported to the TRI.

Second, we examine the extent to which program participation led to an increase in recycling of 33/50 chemicals implying greater use of recycling methods. The amount of 33/50 chemicals transferred off-site for recycling and recycled and recovered at the facility could indicate that firms were using recycling, although detailed information on pollution control methods other than recycling is not available at the facility level. Program participation could cause a faster growth in recycling when program participants used recycling methods to abate direct releases in order to meet their commitments to the program. Program participation could also trigger the adoption of other pollution control methods that reduced releases and recycling of 33/50 chemicals, depending on the costs of recycling vs. other methods. Furthermore, facilities might have to face different costs between conducting on-site recycling themselves and transferring to an off-site recycler. For this reason it is likely that program participation might have affected on-site and off-site recycling differently. Thus we not only examine the effect of program participation on total recycling but also examine on-site and off-site recycling separately.

Last, we examine whether the change in recycling was inversely related to the adoption of P2 technologies. The effect of P2 on recycling of 33/50 chemicals could be ambiguous because it depends on total production and the performance of P2. The use of P2 could reduce the amount of wastes to be recycled if it reduced the generation of pollution at source. However, P2 might also have induced firms to increase total production, which could increase total wastes to be recycled.

To answer these three questions, we undertake the empirical analysis using facility level information on toxic releases, P2 adoption and voluntary program participation of 8756 facilities for the period of 1988 to 1995 in 48 states of the US. We use Generalized Method of Moments

(GMM) estimation with instrumental variables to estimate the effect of P2 and program participation on three types of emissions (releases, on-site and off-site recycling), while controlling for the effects of various regulatory and public pressures on facilities to reduce 33/50 releases and endogenous program participation and P2 adoption.

We find that both program participants and non-participants increased off-site recycling of 33/50 chemicals during the program period. However, program participants had significantly lower rate of increase as compared to non-participants. Meanwhile, program participation had no statistically significant impact on on-site recycling of 33/50 chemicals. These two findings imply that program participants had a statistically significant lower rate of increase in total recycling. We also find that program participation had a statistically significant negative effect on 33/50 releases over and above the effect of P2 adoption. However, the adoption of P2 itself did not reduce 33/50 releases or recycling of 33/50 chemical, except for releases of OD chemicals. Thus participants might have used pollution control methods other than P2 and recycling to reduce releases, but the reduction in release of OD chemicals was primarily through P2.

4.2 Related Literature

Most empirical studies on voluntary environmental initiatives focus on explaining the incentives for firms to voluntarily reduce their TRI emissions. They show that regulatory pressures, negative publicity, and pressure from consumers, local residents, and environmental groups played a significant role in motivating firms to participate in voluntary programs and adopt environmental management systems (Anton, et al., 2004; Khanna, 2006; Khanna et al. 2009; Potoski and Prakash, 2005; Rivera et al., 2006). Several empirical studies have tried to quantify the economic motivations for voluntary reductions in toxic releases and found that high

levels of TRI emissions were associated with low market values (Hamilton, 1998) and TRI reduction led to better financial performance (Hart and Ahuja, 1996; Konar and Cohen, 2001).

Although previous studies have focused on incentives for P2 and determinants of P2 diffusion, few empirical studies have examined the impact of P2 adoption on emissions or analyzed the effectiveness of P2 in comparison to other pollution control methods. A recent study by Harrington et al. (2008) examines the effect of P2 on onsite and off-site emissions and finds that P2 adoption had a statistically significant short term effect on the reduction of on-site releases, but did not significantly reduce cross-media transfers (from on-site releases to off-site disposals and recycling).

A few studies have examined whether there is policy-induced substitution of pollution across media pathways and found mixed evidence. Greenstone (2003) studies the effect of the Clean Air Act Amendments (CAAA) on emissions to air, water and land in iron and steel industry. His research models the percentage change in pollutant releases to air, water, and land with respect to a county's attainment status and finds that CAAA did not induce plants to substitute air release with water or land emission. Alberini (2001) studies the effect of regulation on the substitution between the aboveground and underground gasoline storage tanks in Florida. She finds that the change in the number of underground storage tanks was negatively correlated with change in the number of aboveground storage tanks right after more stringent regulations were imposed on underground storage tanks. Sigman (1996) tests if compliance with air regulations caused facilities to increase off-site transfers for recycling when chlorinated solvents were regulated, and finds that the regulation of air releases reduced the overall reliance on those chemicals, and thus reduced emissions across all media. However, the state tax for incineration had a positive and significant effect in determining the level of air emission, which suggests that

potential cross-media substitution between air releases and offsite recycling can occur when the cost of treatment increases.

Several studies have examined the effectiveness of 33/50 program in reducing 33/50 releases, but the results are mixed. Khanna and Damon (1999) and Innes and Sam (2008) find that the program participation has a statistically significant negative impact on 33/50 releases, with the former study focuses on chemistry sector and the latter on a wide range of manufacturing sectors. Vidovic and Khanna (2007) argue that their finding vanishes if prior reductions in pollution achieved before the start of the program and time and fixed-effects are taken into account. Gamper-Rabindran (2006) focuses only on the 15 non-ozone depleting chemicals, arguing that the two OD chemicals were due to be phased out anyway under the Montreal Protocol. She finds that the impact of the program varied by industry and environmental media. Air releases in certain sectors reduced, while the transfers to off-site recycling facilities increased due to the program. More recently, Sam et al. (2009) find that even after controlling for other voluntary activities a firm might undertake, such as adoption of Total Quality Environmental Management (TQEM) system, program participation had a statistically significant negative impact on 33/50 releases even after participation period ended in 1995.

This paper contributes to the literature in the following ways. First, existing studies on the 33/50 program have focused on examining the extent to which the reduction of 33/50 releases can be attributed to program participation. However, none of them have examined the mechanisms through which this reduction was achieved. Second, this paper uses facility-level data in contrast to other studies that were conducted at the firm level when examining the effectiveness of the 33/50 program with the exception of (Gamper-Rabindran, 2006). Using facility-level data in the analysis enables us to explore the interdependencies between releases,

recycling and P2 adoption at the micro level where these decisions were simultaneously determined by heterogeneous facility characteristics. Last, very few studies have looked at the effectiveness of P2 in reducing emissions. Harrington et al. (2008) examine the effect of P2 on TRI releases, but do not control for particular regulation or voluntary program participation. Sam et al. (2009) study the extent to which 33/50 program participants were more likely to adopt TQEM system, but they do not study any particular pollution control methods as a result of TQEM through which TRI releases are reduced. Unlike Alberini (2001) who observes the substitute technology directly or Sigman (1996) who has a proxy for the cost of alternative technology, we neither observe the costs nor the abatement technology that generate recycling of wastes. We analyze the effects of program participation on emissions to other media (recycling and incineration) to determine the extent to which that program participation might have led firms to adopt other pollution control methods that would result in cross-media transfers. This is an approach similar to Greenstone (2003). In doing so, we also parse out the effect of P2 that could have been motivated by program participation. Our paper not only examines the program's effect on emissions to all media pathways, but also examines the indirect impact of program participation through P2 adoption and P2's effect on emissions to all media pathways.

4.3 Conceptual Framework

We assume that a profit-maximizing facility will simultaneously decide on the optimal level of effort, such as the decision to participate in 33/50 program, type of pollution control method to use, and the extent of pollution reduction to maximize its net benefits. Since these are voluntary activities, a firm will only undertake them to the extent that they are in its self-interest. In the absence of regulations, the implicit reputation costs from adverse publicity associated with the publication of TRI since 1990 have become increasingly important in motivating firms to

reduce emissions beyond the legal mandates. Facilities may also take proactive efforts to preempt future regulations, gain goodwill from regulators and reduce regulatory scrutiny (Harrington, et al., 2008; Khanna, et al., 2009; Sam, 2009). Therefore, facilities that emit higher levels of release from regulated chemicals and face stronger regulatory pressures are more likely to participate in the program. Such facilities may also be more likely to adopt P2 as a way to increase internal efficiency and reduce regulatory scrutiny (Harrington, et al., 2008, Sam, 2009). The extent to which they do so would depend however on the costs of P2 versus other methods of pollution control, such as recycling and reuse.

Program participation could also lead to an increase in recycled wastes when participants shifted greater proportion of emissions from direct releases to recycling facilities. Program participants may have preferred cleaning up at the end-of-pipe, since those methods offer immediate and observable result, do not involve learning costs, and significant investment (Hart and Ahuja, 1996; King and Lenox, 2002). If larger proportion of direct releases were abated using recycling methods, we may find that participants reduced the 33/50 releases but increased recycled wastes as compared to non-participants. The effect of the 33/50 program on total waste becomes unclear when taking into account both direct releases and recycled wastes.

The adoption of P2 technology may not guarantee that direct releases would be reduced. The ambiguity arises because the adoption of P2 has the potential to reduce the intensity of pollution (measured by the pollution per unit of output) and average production cost, thus encourages greater production (Harrington et al., 2008). Since we do not observe total output, the effects of P2 on direct releases need to be empirically determined. On one hand, the adoption of P2 could reduce the use of recycling methods since emissions are prevented through source reduction activities. On the other hand, the adoption of P2 could reduce the cost of production,

which leads to greater production and more recycling. For the above reasons, the direct effect of P2 on recycling cannot be estimated.

The effect of P2 on releases could vary by types of chemicals. Unlike the rest of the 33/50 chemicals, two of the 33/50 chemicals are OD substances and had to be phased out by 1996. This may have created the incentives for firms to apply source reduction methods and to look for substitutes. We may expect a significant negative effect of P2 on releases of OD chemicals, because of the mandatory regulation. The effect of P2 could also vary by toxicity of chemicals. Facilities that process highly toxic chemicals would face greater regulatory and public scrutiny on their toxic emissions thus would be more likely to use P2 to eliminate those chemicals from the TRI.

4.4 Empirical Framework

To examine the extent to which program participation and P2 adoption could lead to reduction in direct releases and emissions to recycling, we use the following equation [4-1] to show that the *ith* facility's emissions at a given year *t* is determined by a vector of facility-specific characteristics X_{it}, the decision of program participation P_{it}, the decision to adopt P2 T_{it}, location and industry specific effects d_i and time effects. λ_t.

$$\Delta y_{it} = \rho \Delta y_{it-1} + \theta_1 \Delta X_{it} + \theta_2 P_{it} + \theta_3 T_{it} + \theta_4 d_i + \theta_5 \lambda_t + \Delta u_{it} \qquad [4\text{-}1]$$

where t=1991,..., 1995 $\Delta y_{it} = y_{it} - y_{it-1}$, $\Delta y_{it-1} = y_{it-1} - y_{it-2}$ $\Delta X_{it} = X_{it} - X_{it-1}$, and $\Delta u_{it} = \Delta u_{it} - \Delta u_{it-1}$[32].

The coefficient for program participation measures the effect of program participation on the change of emissions, which can be interpreted as the difference in the rate of emission

[32] It is possible that the error term still has individual specific effects since program participation variable is not first differenced. The individual effects could be correlated with program participation and the adoption of P2. For this reason, we use instrumental variables for the endogenous program participation and P2 variables.

reduction between participants and non-participants when the dependent variables are in log form. A significant and negative coefficient would imply program participants experienced a greater rate of reduction in emissions than non-participants. The coefficient for the P2 adoption decision indicates the effect of P2 on the rate of change in emissions, after parsing out the effect of other abatement methods through program participation. A significant and negative coefficient would imply that facilities that adopted new P2 would have greater rate of reduction in emissions. We run three versions of equation [4-1], each with a different dependent variable. The three dependent variables are 33/50 releases, on-site recycling of 33/50 chemicals and offsite-recycling of 33/50 chemicals, respectively.

We include the lagged dependent variable in equation [4-1] because several unobserved factors that influence emissions may change slowly over time, such as observe managerial, technical and organizational features of a facility; and emissions are likely to be autoregressive as outputs are autoregressive. However, we do not include lagged recycling when estimating change in recycling using equation [4-1] because we do not find strong autocorrelation in the recycling process probably due to the shorter reporting period[33].

Since the lagged dependent variable in equation [4-1] is correlated with the error term, we use two-year and earlier lags of the dependent variable as GMM instruments(Arellano and Bond, 1991). Furthermore, unobserved facility characteristics could influence both decisions to adopt P2 and to participate in the voluntary 33/50 program and the changes of direct releases and recycling. In order to control for endogenous program participation and P2 variables, we use

[33] Our analysis of the impact of the participation in recycling is constrained to the period 1992-1996, because the reporting of recycling only started in 1991 and taking first difference leaves us observations from 1992 onward. Furthermore, unlike the reporting of direct releases that started with the inception of TRI in 1988, the reporting of recycling was fairly new to TRI facilities at that time. Due to these reasons, we do not find a significant strong autocorrelation in the recycling generating process. For these reasons, we do not include the lagged recycling variable when estimating the effects of P2 and participation on recycling.

instrumental variables Z_1 for P2 adoption and Z_2 for participation when estimating equation [4-1]. To ensure identification, the z variables are hypothesized to influence participation and P2 adoption but are uncorrelated with changes in releases and recycling. In the next section we describe the choice of these variables in detail.

4.5 Variable Construction

4.5.1. Dependent Variables

We define releases as onsite emissions to water, air, land, and transfers to off-site disposals and treatment. We estimate the effects of P2 and program participation on four types of releases: releases of the 33/50 chemicals, releases from OD chemicals, releases from the rest of the 33/50 chemicals, and toxicity-weighted releases of 33/50 chemicals. We refer to them as *33/50 Releases, OD Releases, non-OD Releases* and *Toxicity- Weighted Releases* in the regressions.

Since 1991, TRI facilities have been required to report the quantities of toxic chemicals recycled, treated and used for energy recovery (incineration) on-site and off-site. We estimate the effects of P2 and program participation on three types of recycling:, 33/50 chemicals transferred off-site for recycling and energy recovery, 33/50 chemicals recycled and recovered on-site, and total amount of chemicals for recycling. We refer them as *Total Recycling*, *Off-site Recycling* and *On-site Recycling*. We take logarithm on all of these dependent variables then take the first differences of them and use that as the dependent variable in equation [4-1].

4.5.2. P2 Variables

Firms are required to disclose the number of incremental P2 activities adopted for each chemical to the TRI starting from 1991 onwards. There are 43 types of activities reported and those can be classified into eight broad categories: (1) good operation practices, (2) inventory

control, (3) spill and leak prevention, (4) raw material modifications, (5) process modifications, (6) cleaning and degreasing, (7) surface preparation and finishing, (8) product modifications(Khanna, et al., 2009).

We have two alternative variables to measure the adoption of P2 by a facility (T_{it}). The first one is a binary variable and it equals 1 if a facility had adopted P2 for any of the 33/50 chemicals in a given year, and zero otherwise. We refer to it as *Adopt P2*. We do so because most facilities reported zero P2 activities across all chemicals for a given year. To check for the robustness of our results with respect to this specification, we then aggregate the number of incremental P2 activities across 17 33/50 chemicals for each year by facility and include it in equation [4-1] instead of the binary P2 variable. We refer to it as *Number of P2s* in the regressions.

4.5.3. Other Independent Variables

The binary participation variable (P_{it}) is defined as $P_{is} = 1$ for $t \geq s$ if the facility joined the program in year s, and $P_{is} = 0$ otherwise.

We include the following variables to approximate regulatory pressures, and county and state environmental regulator stringency, as these variables are shown to be correlated with program participation and 33/50 releases in Chapter 2. Specifically, they are *Number of Inspections*, *HAP-TRI ratio*, *County Non-attainment Status*, and *State LCV Scores*. Industry effects are controlled by ten industry dummies, classified by the facility's primary 2-digit SIC code. Time dummies control time effects. Variables to control for location effects include *County Median Income* (in thousand dollars) in which a TRI facility was located.

4.5.4. Endogenous Program Participation and Identification

We use three instrumental variables that are correlated with program participation to identify the effect of program participation in equation [3-1]. They are *First Invitation Group, Facility's Share of Total TRI Releases of the Parent Company*, and *Firm's Prior Change in 33/50 Releases*. In Chapter 2 we have provided a detailed discussion of these three instruments.

4.5.5. Endogenous P2 and Identification

We use the percentage of new P2 adopters in the same industry (excluding the facility itself) and the percentage of P2 adopters in the same county (excluding the facility itself) in the previous period as instruments for the endogenous binary variable *Adopt New P2*. To instrument the endogenous *Number of New P2*s, we use the number of P2 technologies adopted by the facilities in the same county and in the same industry (defined by the 4-digit SIC code) in the last period. We expect these four variables to be correlated with the decision to adopt P2 by a facility due to information spillovers. Since they are based on the characteristics of other facilities, they are not directly correlated with the emissions of at the facility level, except through P2 adoption. Furthermore, the reporting of new P2 adoption started after the program participation and the 33/50 program did not specify any abatement technology, therefore there is no reason to suspect that these variables on neighboring facilities would influence the facility's decision to participate in the program.

4.6 Data Description

TRI provides chemical-specific releases[34], recycling (on-site and off-site), incineration (on-site and off-site), and the number of new P2 adoptions at the facility level. From that, we generate data on 33/50 releases, 33/50 off-site recycling (including recycling and incineration),

[34] Including onsite releases to air, water, injection to land, transfers to treatment and disposal

33/50 on-site recycling, number of P2s adopted, and HAP-TRI ratio. We then use the unique TRI-identifier for each facility to merge this dataset with facility-specific data on the numbers of inspections and penalties for compliance with mandatory air regulations from EPA's AIRS Facility Subsystem (AFS) database (U.S. Environmental Protection Agency, 2007a). We obtain the list of 33/50 participating companies and information about the participation status of each of their facilities through personal communication with Hampshire Research.[35] We are able to use the reported parent company names and Dun and Bradstreet (D&B) numbers to identify the 33/50 participating companies and all their facilities in the TRI. This leads 4123 parent companies, of which 1203 parent companies participated in the 33/50 programs[36]. We then use the list of companies in (33/50 Program office, 1991; U.S. Environmental Protection Agency, 1992) to identify the first invitees of the program and their facilities in the TRI. In addition, we use the location of a facility in the TRI to merge the above data with the county's median income from the 1990 census , the county's attainment status (U.S. Environmental Protection Agency, 2007b), and state-level scores on environmental legislations (League of Conservation Voters, 2007) .

Our final sample has 8756 facilities with 34339 observations for the period of 1991-1995. There are 5804 facilities that belong to 33/50 companies and only 23.6% of them actually participated in the program, rather than 100% assumption made by all previous studies.

During the program period, 49.3% of the 33/50 facilities had adopted P2 at least once, while 36.7% of the non-participating facilities had adopted new P2 at least once. Table 4.1 classifies facilities by number of P2 technologies adopted for program participants and non-

[35] Facility level participation data was obtained from Catherine Miller, Hampshire Research, www.hampshire.org.
[36] The EPA listed 1294 parent companies as participants in the 33/50 program in their final report in 1997. We were unable to find 91 of these parent company names in the 2004 release of TRI database (since some company names may have been updated by the EPA).

participants. We find that program participants tend to adopt more P2s than non-participants. For example, 17.4% of program participants reported to have adopted one P2 technology across all 33/50 chemicals, while only 14.2% non-participants did so; 10.5% of program participants reported to have adopted 5 or more P2 technologies and only 6.4% of non-participants reported five or more P2 technologies.

Figure 4.1 and Figure 4.2 show the average levels of off-site and on-site recycling in the study period. Program participants emitted greater volumes of chemicals through on-site and off-site recycling than non-participants. Both types of recycling activities increased from 1991 to 1996. Off-site recycling increased steadily from 1991 to 1993, but dropped after 1994, especially for program participants.

Summary statistics of variables used in the analysis are presented in Table 4.2. We separate our sample into four groups: program participants and P2 adopters (P=1,T=1), program participants and non-adopters of P2 (P=1, T=0), non-participants and P2 adopters(P=0, T=1) , and non-participants and non-adopters of P2 (P=0, T=0). Table 4.2 shows that program participants adopted greater number of P2 technologies than the non-participants. Program participants were also greater emitters of direct releases and they undertook more on-site recycling and off-site recycling compared to the non-participants. Participants that had not adopted P2 had lower off-site recycling but higher on-site recycling compared to participants that had adopted P2. Only around 4.6% of the sample participated in the program and adopted P2 and the other 5% of the sample participated in the program but did not adopt P2.

4.7 Results

4.7.1. Effects of P2 and Program Participation on 33/50 Releases

Table 4.3 reports the effects of P2 adoption and program participation on 33/50 releases and toxicity-weighted 33/50 releases. All models use the whole set of instrumental variables directly, including the second lagged dependent variable, first invitation group, parent company's prior change in 33/50 releases, facility's share of total TRI releases, and the percentage of P2 adopters in the same industry and in the same county.

Alternatively, we use the number of new P2 adopted, instead of the binary P2 variable in the models reported in Table 4.4, to check for the robustness. To instrument the number of new P2 adopted, we use the average number of P2s adopted by the facilities in the same county and in the same industry (defined by the 4-digit SIC code) in the last period.

Model I in Table 4.3 examines the effects of P2 and participation over the period of 1991-1995, and Model II in Table 4.3 examines the effect of P2 and participation over the period of 1992-1996 (assuming participants remained in the program through 1996). We find that program participants had a greater rate of reduction in 33/50 releases as compared to the non-participants and its statistically significant (Table 4.3, Row 2). This is consistent with the results in Chapter 2 on the effectiveness of the 33/50 program on 33/50 releases. Without taking into account the effect of the adoption of P2, the program participants had a 23% higher rate of reduction (Chapter 2, Table 2.4). Taking into account the effect of P2, the program participants had a 28% higher rate of reduction. This result indicates that program participation had a significant negative effect on 33/50 releases over and above the effect of P2. However, we do not find that adoption of P2 led to a reduction in 33/50 releases. Using the binary variable of P2 adoption, we find that facilities that adopted P2 had a 35.6% lower rate of reduction in 33/50 releases than facilities that did not adopt any P2 (Table 4.3, Row 3, Model I).

Model III and IV examine the program's effect on toxicity-weighted 33/50 releases in 1991-1995 and 1992-1996 respectively. Similar to Model I and II, we find that adoption of P2 did not significantly decrease the toxicity-weighted 33/50 releases and the program's effect was still statistically significant and negative. This implies that the reductions of 33/50 releases and toxicity-weighted 33/50 releases were achieved primarily through abatement efforts other than P2.

In Table 4.4, we use the number of P2s adopted instead of the binary P2 variable. We find that one additional P2 adopted led to a 7.6% increase in the change of 33/50 releases (Model V) and a 9.7% increase in change of toxicity weighted releases (Model VI. The effects of program participation were still statistically negative for the changes of 33/50 releases and toxicity-weighted releases. Program participants had 34.6% higher rate of reduction in 33/50 releases than the non-participants, after taking into account of the number of P2s adopted..

Since the facilities report the adoption of P2 on an annual basis, the exact timing of for P2 to take effect is unclear. Harrington et al. (2008) use facility level data from all TRI facilities over the period of 1991-2001 and find that P2 adopted in the current period had no effect on toxic emissions. However they find that P2 adopted in the last period had a very small but significant negative impact on the toxic emissions of the current period. Nevertheless the impact of P2 is rather limited. For instance, a 1% one-time increase in P2 would result in a 0.032% reduction of releases and a 0.015% reduction of offsite recycling. To check the robustness of our results, we also use the P2 adopted in the last period instead of P2 adopted in the current period in the models[37]. However, that does not affect our conclusions. The magnitudes and directions of the estimated parameter are similar to the ones reported in Table 4.3 and Table 4.4.

37 We include the lagged P2 variable and examine the effects of P2 and program participation for the period of 1993-1996 using the same models as the ones reported in Table 4.3-Table 4.6. Using the lagged P2 leaves us to

Table 4.5 summarizes the results on the effects of P2[38] and program participation on releases of two groups of chemicals. Model IX indicates that the reduction of ODS releases was achieved by adopting P2, while participation did not have any significant effect. In contrast, adoption of P2 had no statistically significant impact on the change of non-OD releases and the reduction of non-OD releases was achieved through program participation (Model X). We use the number of P2s in Model XI and XII and find that an additional P2 technology led to 86% greater rate of reduction for OD chemicals (Model XI). But P2 adoption had no statistically significant impact on change in non-OD releases (Model XII).

In Chapter 2, we find that the program's effect was statistically significant for non-OD releases and was not significant for OD releases (Table 2.5). We hypothesize that both program participants and non-participants had to reduce OD releases by regulation, which explains the finding. In this chapter, we find that the adoption of P2 had a significant negative effect on OD releases. This finding confirms our hypothesis in Chapter 2 that the reduction in OD releases was not directly due to program participation. Particularly the reduction of OD chemicals was achieved by adoption P2 technologies.

4.7.2. Effects of P2 and Program Participation on Recycling of 33/50 Chemicals

We report the estimates on change of recycling wastes in Table 4.6. Model XIII indicates that program participation led to a lower rate of change in total recycling. Specifically, the rate of change on offsite recycling for program participants was 58% lower than for the non-participants. Comparing the volume of offsite recycling wastes before and after the program, Gamper-

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analyze the effect of P2 on releases from 1993 onwards, since we also need to use the lagged P2 from the neighboring facilities as instruments for P2 adopted at the facility level.

[38] The number of P2 adopted for OD chemicals and the number of P2 adopted for non-OD chemicals are considered separately when we examine the P2 effects by groups of chemicals in Table 3.5. Accordingly, we use the percentage of P2 adopters for OD chemicals and for non-OD chemicals in the same industry and in the same county as instruments.

Rabindran (2006) finds that the increase of off-site recycling from program participants was statistically significantly greater than the increase from non-participants. However, she does not find program participants significantly reduced their 33/50 releases, except for two industry sectors. If program paritipants substituted direct releases with off-site recycling, we would observe the changes in these two emissions go in oppsite directions. We find that although program participants sent greater amounts of wastes to recycling facilites and emmitted more releases than non-participants, their average rates of changes for off-site recycling and direct releases were much slower than for non-participants. Using the number of P2s, we find similar results on the effects of P2 and program participation (Model XV). The rate of increase was 51% lower for the participants (Model XVI). However, using either the number of P2s or the binary variable of P2 adoption, we do not find that the adoption of P2 significantly affected the change in off-site recycling (Model XVI and Model XVII, Row 2, and 3). This indicates that program participants might have used pollution control methods other than P2 to reduce both off-site recycling and releases.

We find the effects of HAP-TRI ratio and county median income on off-site recycling to be similar to 33/50 releases. Facilities emitted more HAP releases, and those located in counties with higher income reduced more off-site recycling. In Chapter 2, we find the number of inspections and state LCV scores were positively related to the program participation decision but we do not find the same consistent effects of them on 33/50 releases. However, we find facilities that received greater number of inspections and were located in a state with higher LCV scores transferred more 33/50 chemicals for off-site recycling. This result indicates that stronger regulatory pressures at the state and county level provided incentives for facilities to transfer their wastes to recycling facilities elsewhere. Additionally, we observe an upward trend of off-

site recycling. The time dummies are statistically greater than 1 for all years, indicating every year there was a distinct increase.

Neither program participation nor the adoption of P2 technologies had statistically significant impacts on change in on-site recycling (Model XV and XVIIII). Although variables approximating public pressures and regulatory pressures had statistically significant effects for 33/50 releases and off-site recycling, they did not explain the change in on-site recycling. We also do not find there was a significant time trend in the change of on-site recycling.

4.8 Conclusions

Since both program participation and adoption of P2 technologies are not mandated, firms would only devote their efforts to these voluntary initiatives if they could benefit from them. In Chapter 2, we have focused on the effectiveness of program participation in reducing releases. However, we have not examined the mechanisms through which the reduction was achieved. Firms could have resorted to P2 technologies to reduce pollution from source or used other abatement methods that were lower in the pollution control hierarchy and resulted in cross-media substitution.

This chapter examines the relationship between releases and P2 adoption, and examines the relationship between recycling and P2 adoption. We use facility- and time-specific program participation and P2 information and conduct the analysis for all 33/50 eligible facilities over the period of 1991-1995 (or over 1992-1996 in case of off-site and on-site recycling). We use GMM methods with instrumental variables to examine the effects of program participation and P2 adoption on direct releases and on-site and off-site recycling after controlling for endogenous program participation, P2 adoption and path-dependence of emission generating process.

We find that program participants did not increase transfers to recycling off-site. Despite an upward trend of increase in off-site recycling reported in TRI, we find evidence that the program participants experienced greater rate of reduction in off-site recycling. Additionally, program participants did not show a significant increase in on-site recycling compared to non-participants. Consistent with our finding in Chapter 2, we find that program participants had greater rate of reduction in 33/50 releases than nonparticipants after controlling for the adoption of P2 technologies. These findings indicate that program participation did not cause an increase in total waste from the 33/50 chemicals, as emissions to all media did not increase as a result of the program.

After controlling for other abatement methods through program participation, we find evidence that adoption of P2 slowed the rate of reduction in 33/50 releases. We gain additional understanding on the mechanisms of pollution reduction by conducing the analysis by OD chemicals and the rest of the 33/50 chemicals. Given mandatory phase out, facilities resorted to P2 technologies to reduce the use of OD chemicals. In contrast, the reduction of releases from the rest of the 33/50 chemicals was due to voluntary program participation.

In sum, our findings indicate the interdependency among direct releases, recycling, and P2 methods. The reduction in 33/50 releases was achieved through methods that did not cause an increase in recycling. The effect of P2 technology on releases was ambiguous, except for OD chemicals that were to be eliminated. In the absence of a holistic approach to regulate toxic emissions to all environmental media, policies emphasizing voluntary P2 adoption may not lead to a decrease of total toxic pollution.

4.9 Tables and Figures

Table 4.1 Distribution of Facilities by the Number of New P2 Technologies, 1991-1995.

Number of new P2 technologies adopted	Percentage of Facilities	
	Non-participants	Program Participants
0	61.6	50.7
1	14.2	17.4
2	9.0	10.3
3	4.5	5.6
4	4.2	5.5
5 and more	6.4	10.5
Total	100	100

Table 4.2 Summary Statistics, 1991-1995.

Variables	P=0 & T=0	P=0 &T=1	P=1 & T=0	P=1& T=1
33/50 releases				
(million pounds)	0.060	0.101	0.093	0.138
	(0.252)	(0.302)	(0.345)	(0.437)
Total recycling	0.513	1.942	0.564	1.634
	(5.663)	(24.235)	(4.41)	(10.037)
Offsite recycling				
(million pounds)	0.180	0.236	0.373	0.211
	(1.990)	(1.407)	(2.229)	(0.841)
Onsite recycling				
(million pounds)	0.586	1.235	0.794	1.362
	(8.027)	(15.400)	(6.959)	(9.574)
Number of P2 adopted	0	3.0548	0	3.576
	(0)	(3.067)	(0)	(3.617)
HAP-TRI ratio(Percentage)	74.616	78.021	72.189	75.992
	(32.686)	(29.631)	(33.348)	(30.450)
Number of inspections	0.393	0.409	0.509	0.486
	(1.219	(0.922)	(1.348)	(1.284)
Percentage of P2 adopters				
of the same county	0.189	0.383	0.310	0.383
	(0.208	(0.252)	(0.170)	(0.172)
Percentage of P2				
adopters of the same industry	0.177	0.340	0.298	0.328
	(0.248)	(0.258)	(0.237)	0.247)
Average P2 adopted by				
others in the same industry	49.574	104.818	50.692	135.704
	(124.515)	(174.106)	(123.92)	(226.921)
Average P2 adopted by others in the same county				
	0.5606	0.986	0.582	1.151
	(0.95)	(1.075)	(1.089)	(1.328)
Share in total TRI releases of parent company				
(percentage)	0.316	0.327	0.467	0.475
	(0.404	(0.395)	(0.451)	(0.500)
Firm prior change in 33/50 releases(million pounds)	-0.350	-0.411	-0.934	-0.860
	(1.146)	(1.269)	(2.404)	(2.206)
First invitation group				
(percentage)	0.361	0.394	0.496	0.475
	(0.480)	(0.489)	(0.500)	(0.500)
County non-attainment status	0.935	1.045	1.130	1.181
	(1.1209)	(1.195)	(1.139)	(1.147)
LCV score	95.785	98.412	100.585	102.312
	(38.987)	(39.089)	(39.096)	(36.951)
Number of Observations	20471	12965	1837	1729
Number of Facilities	6765	695	5263	695

Note: Standard errors are in parentheses. We define T=1 if a facility ever adopted any P2 technology in 1991-1995, and 0 otherwise. P=1 if a facility participated in the program in 1991-1995 and 0 otherwise.

Table 4.3 Effects of Program Participation and P2 Adoption on 33/50 Releases, 1991-1996.

Variables	I 33/50 releases	II 33/50 releases	III Toxicity weighted releases	IV Toxicity weighted releases
Lagged releases	0.588***	0.513***	0.716***	0.653***
	[0.060]	[0.060]	[0.061]	[0.061]
Program participation	-0.289**	-0.245**	-0.469***	-0.385**
	[0.113]	[0.100]	[0.163]	[0.152]
Adopt P2 (binary)	0.356*	0.049	0.261	-0.024
	[0.199]	[0.191]	[0.263]	[0.268]
HAP-TRI	-0.010***	-0.010***	-0.016***	-0.015***
	[0.001]	[0.001]	[0.002]	[0.002]
Number of inspections	-0.007	-0.004	-0.012	-0.006
	[0.012]	[0.010]	[0.021]	[0.016]
LCV score	0.003	0.005**	0.004	0.005
	[0.002]	[0.002]	[0.003]	[0.003]
LCV score squared	0	-0.000**	0	0
	[0.000]	[0.000]	[0.000]	[0.000]
Non-attainment status	0.028	0.005	0.058	0.037
	[0.033]	[0.047]	[0.051]	[0.075]
County median income	-0.099***	-0.087***	-0.062	-0.049
	[0.030]	[0.029]	[0.043]	[0.043]
Year 1991	0.622**		0.271	
	[0.294]		[0.425]	
Year 1992	0.806***	0.820***	0.48	0.433
	[0.292]	[0.285]	[0.423]	[0.424]
Year 1993	0.702**	0.731***	0.329	0.294
	[0.292]	[0.283]	[0.422]	[0.422]
Year 1994	0.835***	0.839***	0.565	0.495
	[0.292]	[0.283]	[0.421]	[0.421]
Year 1995	0.763***	0.757***	0.526	0.44
	[0.292]	[0.283]	[0.422]	[0.420]
Year 1996		0.782***		0.438
		[0.285]		[0.423]
SIC 26: Paper	0.031	-0.024	0.04	-0.022
	[0.030]	[0.028]	[0.037]	[0.037]

Table 4.3 (Cont.)

Variables	I 33/50 releases	II 33/50 releases	III Toxicity weighted releases	IV Toxicity weighted releases
SIC 28: Chemical	0.079***	0.033	0.059*	0.036
	[0.024]	[0.023]	[0.031]	[0.033]
SIC 29: Petroleum	0.041	0.051*	0.017	0.088*
	[0.033]	[0.030]	[0.046]	[0.045]
SIC 30: Rubber	-0.004	-0.008	-0.055	-0.043
	[0.026]	[0.029]	[0.036]	[0.042]
SIC 33: Primary metal	0.085*	0.02	-0.022	-0.027
	[0.048]	[0.046]	[0.071]	[0.074]
SIC 34: Fabricated metal	0.037	-0.023	-0.06	-0.065
	[0.034]	[0.032]	[0.048]	[0.051]
SIC 35: Machinery & computer	-0.04	-0.035	-0.156***	-0.086
	[0.038]	[0.037]	[0.058]	[0.064]
SIC 36:Electronics	-0.113***	-0.123***	-0.191***	-0.182***
	[0.029]	[0.030]	[0.044]	[0.046]
SIC 37:Transportation	-0.008	-0.049*	-0.072*	-0.106**
	[0.025]	[0.027]	[0.038]	[0.044]
SIC 38: Instruments	-0.127**	-0.075	-0.247***	-0.092
	[0.054]	[0.052]	[0.087]	[0.085]
Number of facilities	8756	8119	34,339	32,069
Observations	34,339	32,069	8756	8119
R-squared	-0.498	-0.422	-0.652	-0.578
Hansen' J statistics	11.62	9.005	13.47*	13.39**
Number of over identified conditions	7	6	7	6
Weak ID test	10.08**	9.679**	12.87***	11.63***

Note: Model I and III examine the period of 1991-1995 while Model II and IV examine the period of 1992-1996 (assuming program participants remained in the program in 1996). We use GMM with instrumental variables for the lagged dependent variable and endogenous program participation and P2 adoption variables, using a pooled panel dataset. The adoption of P2 is defined as a binary choice. Robust standard errors are in brackets and they are clustered at the facility level. *** p<0.01, ** p<0.05, * p<0.1.

Table 4.4 Alternative Specifications Evaluating the Effects of P2 and Program Participation on 33/50 Releases and Toxicity Weighted Releases, 1991-1996.

Variables	V 33/50 releases	VI Toxicity weighted releases	VII 33/50 releases	VIII Toxicity weighted releases
Lagged releases	0.591***	0.747***	0.553***	0.705***
	[0.036]	[0.036]	[0.039]	[0.039]
Program participation	-0.346***	-0.595***	-0.275***	-0.420***
	[0.113]	[0.173]	[0.100]	[0.157]
Number of P2s	0.076***	0.097***	0.037*	0.048
	[0.019]	[0.027]	[0.020]	[0.029]
HAP-TRI	-0.010***	-0.016***	-0.010***	-0.016***
	[0.001]	[0.002]	[0.001]	[0.002]
Number of inspections	-0.008	-0.015	-0.005	-0.008
	[0.012]	[0.021]	[0.010]	[0.016]
LCV score	0.003	0.004	0.005**	0.005
	[0.002]	[0.003]	[0.002]	[0.004]
LCV score squared	0	0	-0.000**	0
	[0.000]	[0.000]	[0.000]	[0.000]
Non-attainment status	0.031	0.056	0.006	0.036
	[0.032]	[0.051]	[0.048]	[0.077]
County median income	-0.092***	-0.062	-0.089***	-0.056
	[0.028]	[0.042]	[0.028]	[0.042]
Year 1991	0.604**	0.25		
	[0.291]	[0.435]		
Year 1992	0.792***	0.465	0.822***	0.435
	[0.289]	[0.433]	[0.286]	[0.427]
Year 1993	0.687**	0.319	0.732***	0.297
	[0.289]	[0.432]	[0.284]	[0.425]
Year 1994	0.813***	0.554	0.842***	0.507
	[0.289]	[0.431]	[0.283]	[0.424]
Year 1995	0.739**	0.519	0.763***	0.461
	[0.289]	[0.431]	[0.284]	[0.424]
Year 1996			0.794***	0.464
			[0.285]	[0.426]

Table 4.4 (Cont.)

Variables	V 33/50 releases	VI Toxicity weighted releases	VII 33/50 releases	VIII Toxicity weighted releases
SIC 26: Paper	0.058*	0.075*	-0.018	-0.014
	[0.030]	[0.040]	[0.029]	[0.039]
SIC 28: Chemical	0.042**	0.019	0.019	0.024
	[0.021]	[0.030]	[0.021]	[0.029]
SIC 29: Petroleum	-0.036	-0.08	0.011	0.04
	[0.041]	[0.058]	[0.037]	[0.058]
SIC 30: Rubber	0.011	-0.043	-0.006	-0.039
	[0.026]	[0.036]	[0.028]	[0.041]
SIC 33: Primary metal	0.081**	0.018	0.038	0.024
	[0.032]	[0.048]	[0.031]	[0.049]
SIC 34: Fabricated metal	0.047*	-0.027	-0.008	-0.029
	[0.028]	[0.041]	[0.028]	[0.042]
SIC 35: Machinery & computer	-0.025	-0.117**	-0.015	-0.038
	[0.034]	[0.052]	[0.033]	[0.055]
SIC 36:Electronics	-0.075**	-0.145***	-0.107***	-0.152***
	[0.031]	[0.047]	[0.032]	[0.049]
SIC 37:Transportation	-0.003	-0.064	-0.049*	-0.095**
	[0.025]	[0.039]	[0.027]	[0.044]
SIC 38: Instruments	-0.082	-0.199**	-0.063	-0.075
	[0.052]	[0.088]	[0.051]	[0.087]
Number of facilities	8756	34,339	8119	32,069
Observations	34,339	8756	32,069	8119
R-squared	-0.501	-0.708	-0.48	-0.664
Hansen' J statistics	13.14*	16.21**	9.791	13.44**
Number of over identified conditions	7	7	6	6
Weak ID test	13.84**	17.76***	15.64**	18.49***

Note: Different from Table 4.3 in which a binary variable of P2 adoption is used, all models use the number of P2 adopted as an explanatory variable. We use GMM with instrumental variables for the lagged dependent variable and endogenous program participation, and P2 adoption variables, using a pooled panel dataset. We perform GMM with instrumental variables to estimate the above models on a pooled panel dataset. Robust standard errors in brackets (clustered at facility level). *** p<0.01, ** p<0.05, * p<0.1.

Table 4.5 Effects of Program Participation and P2 adoption on OD releases, and Non-OD Releases, 1992-1996.

Variables	IX OD releases	X Non-OD releases	XI OD releases	XII Non-OD releases
Lagged releases	0.602***	0.407***	0.656***	0.429***
	[0.033]	[0.068]	[0.032]	[0.047]
Program participation	-0.044	-0.137	0.018	-0.128
	[0.104]	[0.113]	[0.105]	[0.108]
Adopt P2 (binary)	-1.759***	-0.026		
	[0.181]	[0.213]		
Number of P2s			-0.861***	0.006
			[0.104]	[0.020]
HAP-TRI	-0.001	-0.007***	-0.001*	-0.007***
	[0.001]	[0.001]	[0.001]	[0.001]
Number of Inspections	-0.001	0.001	0	0
	[0.015]	[0.010]	[0.016]	[0.010]
LCV score	-0.003	0.003	-0.003	0.003
	[0.003]	[0.002]	[0.003]	[0.002]
LCV score squared	0	-0.000**	0	-0.000**
	[0.000]	[0.000]	[0.000]	[0.000]
Non attainment status	0.067	0.002	0.061	0.007
	[0.055]	[0.051]	[0.056]	[0.051]
County median income	0.067*	-0.069**	0.053	-0.069**
	[0.034]	[0.032]	[0.036]	[0.031]
Year 1992	-0.660*	0.626*	-0.546	0.621*
	[0.346]	[0.346]	[0.358]	[0.322]
Year 1993	-0.765**	0.790**	-0.646*	0.780**
	[0.347]	[0.346]	[0.359]	[0.321]
Year 1994	-0.671*	0.680*	-0.543	0.668**
	[0.348]	[0.351]	[0.360]	[0.322]
Year 1995	-0.658*	0.529	-0.528	0.518
	[0.350]	[0.349]	[0.362]	[0.322]
Year 1996	-0.654*	0.613*	-0.516	0.608*
	[0.350]	[0.345]	[0.362]	[0.321]

Table 4.5 (Cont.)

Variables	IX OD releases	X Non-OD releases	XI OD releases	XII Non-OD releases
SIC 26: Paper	-0.007	-0.067**	-0.009	-0.071**
	[0.036]	[0.031]	[0.034]	[0.032]
SIC 28: Chemical	-0.001	-0.011	0.006	-0.015
	[0.022]	[0.024]	[0.023]	[0.021]
SIC 29: Petroleum	-0.091*	0.029	-0.088*	0.02
	[0.048]	[0.030]	[0.052]	[0.035]
SIC 30: Rubber	-0.104***	0.061*	-0.124***	0.059*
	[0.039]	[0.036]	[0.039]	[0.035]
SIC 33: Primary metal	-0.049*	0.019	-0.04	0.023
	[0.026]	[0.048]	[0.027]	[0.033]
SIC 34: Fabricated metal	-0.038	0.032	-0.03	0.034
	[0.025]	[0.034]	[0.025]	[0.030]
SIC 35: Machinery & computer	-0.078**	0.034	-0.080**	0.036
	[0.035]	[0.041]	[0.035]	[0.038]
SIC 36:Electronics	-0.054	-0.05	-0.058	-0.049
	[0.035]	[0.035]	[0.037]	[0.036]
SIC 37:Transportation	0.022	-0.002	-0.002	-0.002
	[0.037]	[0.034]	[0.038]	[0.032]
SIC 38: Instruments	0.182**	0.081	0.202**	0.078
	[0.078]	[0.053]	[0.090]	[0.053]
Number of facilities	8119	8119	8119	8119
Observations	32,069	32,069	32,069	32,069
R-squared	-0.475	-0.306	-0.548	-0.332
Hansen' J statistics	98.39***	12.66*	99.78***	11.18*
Number of over identified conditions	6	6	6	6
Weak ID test	38.22***	8.818*	33.92***	17.6***

Note: Models IX and X use the binary variable of P2 as explanatory variable and Models XI and XII use the number of P2 adopted as explanatory variable . We perform GMM with instrumental variables for the lagged releases, program participation and P2 adoption variables. The estimations are conducted on a pooled panel dataset. Robust standard errors in brackets (clustered at facility level). *** p<0.01, ** p<0.05, * p<0.1.

Table 4.6 Effects of P2 and Program Participation on Recycling, 1992-1996.

Variables	XIII Total recycle	XIV Offsite recycle	XV Onsite recycle	XVI Total recycle	XVII Offsite recycle	XVIII Onsite recycle
Program participation	-0.490**	-0.588***	0.234	-0.373*	-0.521***	0.134
	[0.209]	[0.210]	[0.212]	[0.192]	[0.195]	[0.200]
Adopt new P2 (binary)	0.610*	0.29	-0.208			
	[0.337]	[0.349]	[0.351]			
Number of P2s				0.056	0.025	0.03
				[0.036]	[0.038]	[0.041]
HAP-TRI	-0.003***	-0.002**	-0.001	-0.003***	-0.002**	-0.001
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Number of inspections	-0.003***	0.027**	0.001	0.011	0.027**	0
	[0.001]	[0.013]	[0.014]	[0.011]	[0.013]	[0.014]
LCV score	0.005**	0.006**	0.004	0.005*	0.005*	0.004
	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]
LCV score squared	0	0	-0.000*	0	0	-0.000*
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Non attainment status	-0.049	-0.082	-0.035	-0.037	-0.076	-0.038
	[0.058]	[0.063]	[0.060]	[0.057]	[0.062]	[0.060]
County median income	-0.198***	-0.175***	-0.026	-0.170***	-0.162***	-0.052
	[0.056]	[0.057]	[0.058]	[0.049]	[0.051]	[0.053]
Year 1992	1.830***	1.794***	0.418	1.726***	1.759***	0.55
	[0.526]	[0.530]	[0.543]	[0.500]	[0.513]	[0.532]
Year 1993	1.748***	1.773***	0.242	1.635***	1.733***	0.38
	[0.526]	[0.531]	[0.544]	[0.499]	[0.512]	[0.531]
Year 1994	1.727***	1.732***	0.224	1.603***	1.686***	0.368
	[0.527]	[0.531]	[0.545]	[0.499]	[0.511]	[0.531]
Year 1995	1.618***	1.596***	0.204	1.480***	1.543***	0.359
	[0.530]	[0.535]	[0.548]	[0.499]	[0.512]	[0.532]
Year 1996	1.557***	1.452***	0.245	1.419***	1.401***	0.403
	[0.532]	[0.537]	[0.549]	[0.500]	[0.514]	[0.533]
SIC 26: Paper	-0.027	-0.024	-0.011	-0.02	-0.021	-0.006
	[0.056]	[0.060]	[0.075]	[0.053]	[0.059]	[0.076]
SIC 28: Chemical	0.175***	0.117***	0.067	0.128***	0.096**	0.070*
	[0.043]	[0.043]	[0.046]	[0.038]	[0.039]	[0.041]

Table 4.6 (Cont.)

Variables	XIII Total recycle	XIV Offsite recycle	XV Onsite recycle	XVI Total recycle	XVII Offsite recycle	XVIII Onsite recycle
SIC 29: Petroleum	0.169**	0.109*	0.157**	0.112	0.088	0.127
	[0.067]	[0.064]	[0.071]	[0.076]	[0.075]	[0.083]
SIC 30: Rubber	0.027	-0.055	0.166***	0.056	-0.041	0.161***
	[0.052]	[0.050]	[0.051]	[0.048]	[0.048]	[0.049]
SIC 33: Primary metal	0.341***	0.245***	0.033	0.267***	0.209***	0.098
	[0.085]	[0.085]	[0.085]	[0.060]	[0.060]	[0.060]
SIC 34: Fabricated metal	0.269***	0.184***	-0.03	0.241***	0.170***	0.004
	[0.053]	[0.053]	[0.055]	[0.044]	[0.044]	[0.046]
SIC 35: Machinery & computer	0.152***	0.047	-0.056	0.139***	0.038	-0.026
	[0.056]	[0.055]	[0.055]	[0.052]	[0.052]	[0.053]
SIC 36:Electronics	0.04	0.026	-0.086	0.075	0.043	-0.078
	[0.048]	[0.052]	[0.056]	[0.048]	[0.053]	[0.059]
SIC 37:Transportation	0.072	0.023	-0.055	0.081*	0.027	-0.059
	[0.047]	[0.047]	[0.047]	[0.045]	[0.046]	[0.047]
SIC 38: Instruments	-0.035	-0.007	0.002	0.041	0.032	-0.025
	[0.081]	[0.079]	[0.110]	[0.065]	[0.064]	[0.102]
Number of facilities	8119	8119	8119	8119	8119	8119
Observations	32,069	32,069	32,069	32,069	32,069	32,069
R-squared	-0.013	-0.003	-0.001	0.001	0.001	0.002
Hansen' J statistics	1.838	1.789	6.763*	4.523	4.194	7.397*
Number of over identified conditions	3	3	3	3	3	3
Weak ID test	15.68***	15.68***	15.68***	19.95***	15.68***	19.95***

Note: Models XIII and XV use the binary variable of P2 as explanatory variable and Models XVI and XVIII use the number of P2 adopted as explanatory variable. We perform GMM with instrumental variables for program participation and the P2 variables to estimate using a pooled panel dataset. Robust standard errors in brackets (clustered at facility level). *** p<0.01, ** p<0.05, * p<0.1.

Figure 4.1 Average Off-site Recycling, 1991-1996.

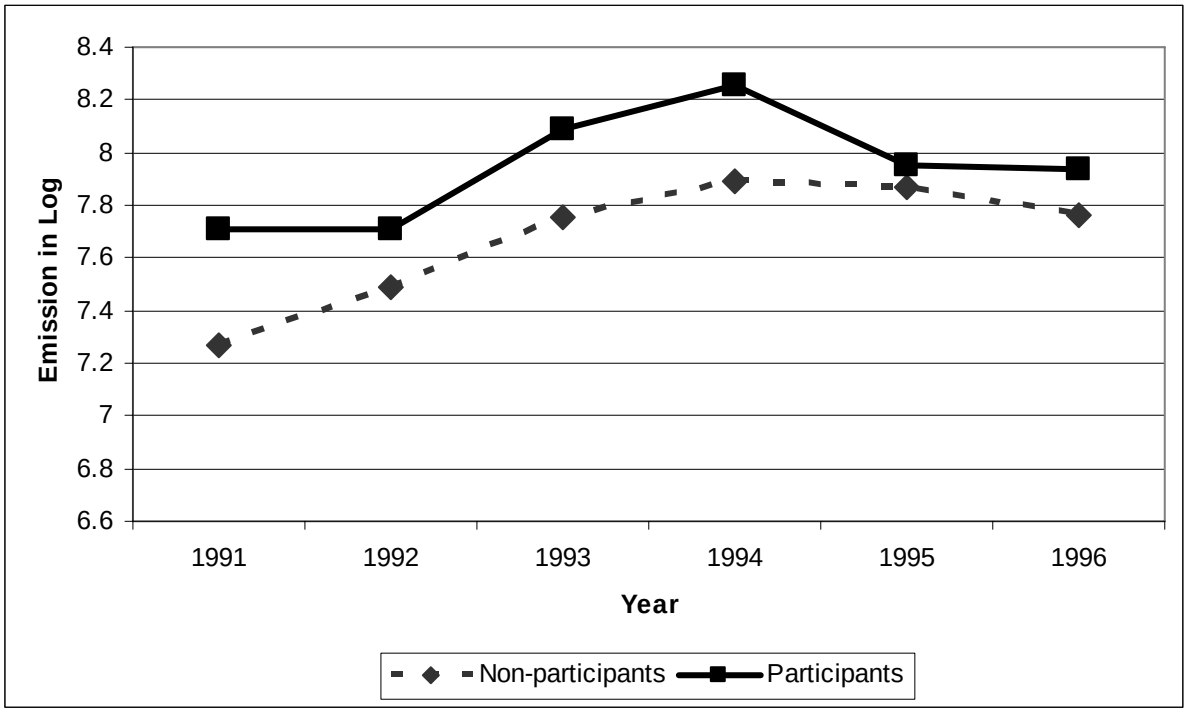
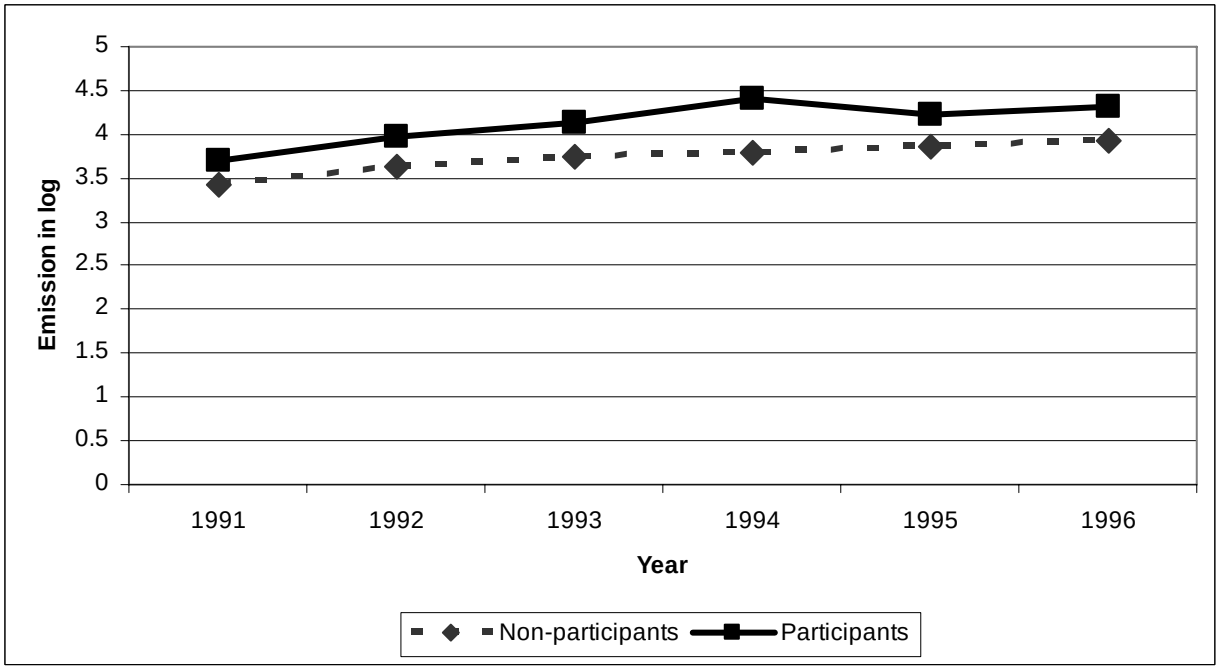


Figure 4.2 Average On-site Recycling, 1991-1996.



Chapter 5 Conclusions

5.1 Summary of Findings

Complex industrial manufacturing activities use millions of pounds of toxic chemicals every year in the U.S. Though the usage, storage, and disposal of those toxic chemicals could pose potential environmental and health risks, designing and enforcing mandates on numerous production processes and toxic pollutants could be administratively difficult and costly to the regulators. Instead, the government has sought to use more cost effective and incentive-based policy instruments to encourage environmental stewardship among firms. In response to the deadly chemical leak in Bhopal, India and serious chemical release accident in West Virginia, the U.S. government has mandated public information disclosure on the usage, disposal and emissions of toxic chemicals, to increase industry transparency and public awareness. Additionally, the government has also initiated voluntary programs, established information exchange platforms and invested in outreach efforts to promote P2 technology to reduce toxic emissions.

This dissertation examines the effects of information and incentive based approaches on a firm's environmental performances and the firm's adoption of environmental technology. In Chapter 2, we evaluate the effectiveness of the EPA's voluntary 33/50 program in reducing the 33/50 releases. We analyze 8756 facilities, over the period of 1991-1999, using dynamic panel data models to incorporate facility specific unobserved effects, path dependence of the emissions generating process and timing of participation, while controlling for endogeneity of program participation. Results show that the program reduced overall and toxicity-weighted 33/50 releases, but the effect is much smaller compared to estimation using firm-level participation

data. We also find that the program effect differed across the 17 chemicals. The program had a statistically insignificant impact on two ozone-depleting chemicals, but a statistically significant negative impact on the remaining 15 chemicals.

In Chapter 3, we examine the extent to which information spillovers motivated the adoption of P2 technologies. We further examine the extent to which program participation increased the adoption of P2 technologies for participants and whether higher participation ratio in the neighborhood was associated with greater P2 adoption. We conduct the empirical analysis on 6974 facilities that were eligible for the 33/50 program from 1991 to 1995. We estimate the number of P2 technologies adopted for 33/50 chemicals and other TRI chemicals at the facility level with respect to program participation, compliance costs to regulations, prior P2 experience by the neighbors on the respective chemicals, and the program participation ratio in the neighborhood. We address the endogeneity of program participation with instrumental variables, and control for location and industry fixed effects. We find that facilities were more likely to learn about adoption of P2 technologies from their industry peers. The direct impact of program participation was only evident for 33/50 chemicals. The presence of program participants did not significantly motivate P2 adoption in the neighborhood.

In Chapter 4, we examine the extent to which program participation led 33/50 facilities to use recycling methods and the extent to which P2 adoption led to reductions in releases and recycling of 33/50 chemicals. We undertake this analysis using the same sample as in Chapter 2. We evaluate three outcomes of interest: on-site recycling, off-site recycling and direct releases while controlling for endogenous program participation and P2 adoption as well as the effects of various regulatory and public pressures on facilities to reduce 33/50 releases. Consistent with our finding in Chapter 2, we find that program participants had greater rate of reduction in 33/50

releases than nonparticipants after controlling for the adoption of P2 technologies. Despite an upward trend of increase in off-site recycling reported in TRI, we find evidence that the program participants experienced lower rate of increase in off-site recycling. Additionally, program participants did not show a significant increase in on-site recycling compared to non-participants. These findings indicate that program participation did not cause an increase in total emissions from the 33/50 chemicals, as emissions to all media did not increase as a result of the program. However, after controlling for program participation, the adoption of P2 technology did not reduce releases and recycling of 33/50 chemicals, except for the releases of ozone depleting chemicals. The reduction in releases of ozone depleting chemicals was due to adoption of P2 technologies instead of directly due to program participation.

5.2 Implications for Future Research and Policy

Previous studies on the effectiveness of the 33/50 program have yielded mixed results. These studies have used data aggregated at the firm level or assumed that all facilities were program participants if their parent companies had participated in the program. In Chapter 2, we find that there was great extent of heterogeneity among facilities of the same parent companies. With a firm with multiple plants, we find that the incentives to participate in the program were greatly reduced once one of the plants had participated in the program. We show that making the same assumption as previous studies leads to an attenuated estimate of the program's effect. Since TRI facilities meet the minimum reporting thresholds, they are larger emitters of toxic pollutants, and therefore are more likely to make decisions on emissions, program participation, and technology adoption at the facility level. Thus, our study highlights the importance of undertaking the analysis at a disaggregated level for future studies using data from the TRI.

Although program participants had reduced more 33/50 releases than non-participants, we find in Chapter 4 that the reduction was not directly achieved through P2 adoption. Policymakers have emphasized their preference for P2 over other abatement methods in the pollution control hierarchy. However, we do not find evidence that the adoption of P2 reduced 33/50 releases or recycling, except for ozone depleting chemicals. To the best of our knowledge, Harrington et al. (2008) is the only other empirical evaluation of the effect of P2 on toxic emissions. The authors use facility level data from all TRI facilities over the period of 1991-2001 and find that current period P2 adoptions had no effect on toxic emissions. Although they find that one-year lagged P2 significantly reduced toxic emissions of the current period, the magnitude of the impact was very small. Both our analysis and that of Harrington et al. (2008) suggest that P2 technologies may not significantly decrease total toxic pollution, since it may have enabled firms to produce more output through increasing production efficiency. Our findings thus suggest that voluntary P2 efforts may not lead to a decrease in total toxic emissions without a cap on total toxic emissions.

Our analysis of the adoption of P2 for 33/50 chemicals and other chemicals by 33/50-eligible facilities show that facilities in the same industry were more likely to learn from each other, but facilities from the same county were less likely to do so. This result suggests that, in the TRI dataset, there could be greater similarities between industry neighbors than between geographic neighbors. Thus, facilities might have stronger incentives to adopt P2 either to imitate their industry peers or to learn how to better use a technology from industry peers. Due to data limitation, we have assumed that facilities in the same industry and in the same county are more likely to learn from each other, and we have treated the neighbors from the same county and the same industry as equally important. Our results suggest two possible extensions that

future studies could explore. First, information from industry peers should probably be given greater weight than information from the geographic neighbors when examining adoption and diffusion of environmental technology. Second, we do not have information on the supply chains through which facilities are connected. Within the same industry, facilities may have learned more from the peers with whom they share common suppliers or end-users. Thus, those peers should be given greater weight than the rest of the facilities in the industry. Future policies to encourage information exchange should thus focus on those firms that are most related to each other.

Furthermore, existing literature also shows that there are two types of information generated by early adopters: information on how to effectively use a new technology and information on the benefit of the new technology (Kremer and Miguel, 2007; Oster and Thornton, 2009). The former tends to increase the adoption rate, especially when a technology is difficult to use but the benefit is certain. The effect of the latter depends on the effectiveness of the technology. Our data do not allow us to distinguish between these types of information. Future research could provide more insights on the role of information spillover on environmental technology adoption by investigating the two types of information explicitly. For example, future research could identify two types of technologies: technologies with uncertain performance and technologies that are difficult to use, to compare the effects of spillovers on the adoption of these technologies.

5.3 Final Remarks on Voluntary Program

As the first public voluntary initiative, the 33/50 program has been extensively studied by scholars. We conduct a comprehensive analysis of the role of the 33/50 program in motivating pollution reduction, adoption of P2 technologies, and inducing adoption of P2 technologies

among neighboring facilities. The 33/50 program motivated the reduction of 33/50 releases and reduced the rate of increase in off-site recycling. Program participation also motivated the adoption of P2 technologies for 33/50 chemicals but not for other TRI chemicals. Facilities were not motivated to adopt more P2 technologies even if there were more participants in their geographic and industrial networks. Despite the policy emphasis on P2, the adoption of P2 technologies did not reduce toxic releases, except for ozone depleting chemicals that were to be phased out. We conclude that the effects of the 33/50 program were limited to the targeted chemicals and program participants. Thus voluntary programs by themselves may not be a sufficient to address a wide range of toxic pollution problems and induce diffusion of environmental technology.

Our findings suggest that future voluntary policies could be improved in two ways. First, the 33/50 program had a clear cap on direct releases but did not specify reduction in total toxic wastes. Policy makers could set up a cap on total toxic emissions (including releases, recycling, and disposal) for the chemicals[39] with higher toxicity to reduce the overall dependence on those chemicals and induce environmental technology change. Second, the 33/50 program was intended to encourage the P2 ethic but did not set up mechanisms to systematically measure the progress and the effectiveness of P2 technology. Though EPA published a few successful cases on reduction efforts in the 33/50 program report (U.S Environmental Protection Agency, 1995), it remains unclear the extent to which those process innovations and modifications were disseminated among program participants. Furthermore, the existing reporting of P2 activities in the TRI may not be sufficient since it does not indicate when those activities are effectively implemented or even discontinued. Future voluntary programs on toxic pollutions could utilize

[39] The EPA has evaluated the toxicity characterization for chemicals of High Production Volume, and set up challenge program to challenge firms to make the data on these chemicals public available. A cap on these HPV chemicals could be considered.

the existing P2 information clearinghouse to record the progress in adoption and implementation of new technologies. Last, the effect of information spillover depends on the effectiveness of the new technology. To effectively disseminate a new technology, future voluntary programs could provide information subsidies to a few early adopters in order to observe the effectiveness of the new technologies and identify the most effective technologies. To leverage the effect of information spillover, future programs could target those information subsides to companies that are closely related to other firms in their respective industries.

In the absence of a regulation on Greenhouse gas (GHG) emissions, the EPA initiated the GHG Reporting Program in 2010. Starting in 2011, major sources of CO2 emissions are required to disclose their emissions through the program that covers more than 10,000 facilities in the U.S. The program "intends to provide accurate and timely data to inform future climate policies without requiring control of GHG" (U.S. Environmental Protection Agency, 2010c). Our study on the 33/50 program, TRI and P2 may have the following implications for future policies GHG reduction policies in the U.S.

First, firms were motivated to reduce their toxic emissions following the first publication of the TRI. It is likely that the disclosure of GHG emissions could also motivate voluntary offset efforts and provide incentives for firms to participate in a voluntary program to reduce GHG emissions. Additionally, the accurate reporting and publication of GHG emissions could provide a foundation to establish a voluntary carbon market. With the publication of GHG emissions, larger emitters may have stronger incentives to voluntarily report their abatement and participate in offset markets in order to reduce pressures from consumers and environmental groups. There could also be an increasing trend of third party verification on offset efforts. Evidence shows that third party certification on the environmental management system instilled changes in

environmental management philosophy and practices (Arimura, et al., 2008; Harrington, et al., 2008; Sam, et al., 2008). To push for further reduction in GHG emissions, EPA could include those voluntary efforts in the GHG reporting system, provided that they meet third party verification.

Second, unlike other unsuccessful voluntary programs, the 33/50 program can be evaluated because its baseline and the outcome are both measurable using the existing toxic releases data in the TRI. The establishment of the GHG reporting program could provide policy makers with the necessary baseline information on GHG emissions to design voluntary programs to control GHG emissions. However, the current GHG reporting system excludes activities such as CO2 injections and geological sequestration. Though these methods prevent CO2 from being released into the atmosphere, large emitters may have stronger incentives to reduce their total reported quantity by claiming that they are using CO2 injections and geological sequestration to limit their actual environmental releases. Following the example of the TRI that includes recycling and direct releases, the reporting system could create two separate categories: total GHG emissions directly released to the environment and GHG released through injection and sequestration. This would provide a complete baseline on the total GHG generated to the researchers, environmental groups and the public.

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